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Locality Repulsion Projection and Minutia Extraction Based Similarity Measure for Face Recognition

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Abstract-
Face recognition technology is the least intrusive and fastest biometric technology.It works with the most individual identifier.In face recognition most of the previous matching strategies fail to discriminative feature extraction with one sample per class as the gallery data(SSPP).Locality repulsion projections(LRP) is the face recognition method that address the problem of single sample per person(SSPP).Similar face images from different people may lie in a locality in the feature space and cause misclassification.The LRPmethod is aimed to separate the samples of different classes within a neighborhood through subspace projections for easier classification.Sparse reconstruction-based similarity measure (SRSM) measures the similarity between each gallery face and the probe image set.Additionally minutiae extraction is implemented for accurate representation of the image is critical to automatic identification systems,because most deployed commercial large-scale systems are dependent on feature-based matching (correlation based techniques).Among all the features,minutia point features with corresponding orientation maps are unique enough to discriminate amongst facial images robustly; the minutiae feature representation reduces the complex recognition problem to a point pattern matching problem.In Experimental results on five widely used face datasets are presented to demonstrate the effectiveness of the proposed approach.
Key Terms—Face recognition,image-to-set matching, locality repulsion projections (LRP),and Minutiae extraction

I. INTRODUCTION

Face recognition systems such as law enforcement, e-passport, and ID card identification,there is usually only a single sample per person (SSPP) in recognition systems because it is normally difficult to collect additionalsamplesunder discriminative feature. In face recognition systems, the probe samples of images are captured on the spot, and it is possible to collect multiple face images per person for on-location probing.We define this problem as image-to-set face recognition in this paper.

In this paper LRP and sparse reconstruction based similarity measure (SRSM) methods for face recognition from SSPP.The LRP method is motivated by our observation that similar face images from different people may lie in a Locality and causes misclassification.LRP method aimed at repulse the samples of their close neighbors of different classes during subspace projection so that they are distinctly separated from each other for accurate recognition.To better characterize the similarity between each gallery face and the probe image set instead of comparing pairs of images, we propose an SRSM method to better assign a label to each probe image set as a whole.

To improve recognition accuracy, let the samples in a locality repulse each other during projection so that they are more discriminative in the low-dimensional LRP feature subspace. As a result, the distances between interclass samples should become more uniform to facilitate the subsequent classification task.To better characterize the similarity between each gallery face and the probe image set, SRSM method is used for assigning a label to each probe image set.Five publicly available face databases used namely,AR CMU PIE , Extended Yale B, and FERET,LFW were used for experiments to demonstrate the effectivenessof our proposed approach for controlled image-toset face recognition.

II. EXISTING SYSTEM

The challenges of face recognition mainly come from the large variations inthe visual stimulus due to illumination conditions, viewing directions, facial expressions, aging, and disguises.Within the past two decades, numerous face recognition methods have been proposed to deal with these challenging problems,various methods such as Eigen (PCA) features, Gabor features, and local binary features. Eigen features are probably the most widely adopted local features, possibly due to the early success of the holistic Eigen face method.However, as has been clearly articulated both for general pattern classification problems and specifically for facerecognition ,PCA is designed for representing pattern for recognition requires discriminative features. Another drawback of Eigen features is that they require a training set to construct a subspace.

For the NND method, the geometrical information of the set is not utilized to calculate the similarity score because the image-to-set distance is converted into the image-to-image distance directly and the smallest one is selected as the image-to-set distance.

For the KNNS method,there is a tuning parameter K in the K-nearest neighbors of a gallery sample,which is difficult to optimize and is usually empirically set.In fact the neighborhood with different number of samples is usually better than a fixed number of samples to characterize similarity of a sample and a set. Hence, this metric is not data adaptive and is also sensitive to noise.

III. PROPOSED SYSTEM

In image-to-set face recognition problem, there is only a single gallery image for each person, but there is a probe set of multiple images.

Let X = [x1, x2…,xN] be the gallery images, x i is the gallery image of the ith person, where l is the feature dimension of each face sample, and N is the number of persons in the gallery. Assume that Z = [z1, z2, ・・・,zM] is the probe image set containing M face images from the same subject

A. LRP

LRP method provides a new perspective in solving the image-to-set face recognition problem. The basic ideaof the proposed LRP method is the distributions between a sample (S1) and its three local neighbors (S2, S3, and S4) in the original image.It can be seen that the distance between S1 and S2 (d12) is much larger than d13 and d14. Hence, probe images from Class 1 are more easily misclassified into Class 3 or Class 4 than Class 2.

To make such misclassifications less likely, aim to learn a mapping to project these samples into a low-dimensional feature subspace to enlarge the initially short distances d _ 13 and d _14, while maintaining a reasonably large d_12. Feature can be extracted from various projection viewed by feature extraction. It used to reduce the ref data base. It also extract invariant feature.

B. SRSM

SRSM method for identifying the unlabeled persons between a gallery image and a probe set.Z = [z1, z2, ・・・,zM] test image set consisting of M image samples. There are a number of possible ways to calculate the distance between low-dimensional of probe image set Z and the gallery image xi.

C.Image Read and pre-processing

Image can be read from computer disk. Normal image has three dimensional data. In the pre-processing stage three dimensional data into two dimensional data

D.Color transform

Given dark RGB color can be converted in to YCBCR.This color space represents each color with 3 numbers similarly as the RGB space.The Y component represents the intensity of the light.The Cb and Cr components indicate the intensities of the blue and red components relative to the green component.This color space exploits the properties of the human eye.The eye is more sensitive to light intensity changes and less sensitive to hue changes. When the amount of information is to be minimized, the intensity component can be stored with higher accuracy than the Cb and Cr components.The JPEG file format makes use of this color space to throw away unimportant information.

E.Sparse Reconstruction

Received image on various projection, so can't match ref data base .Sparse reconstruction process constructs the image into various.Sparse reconstruction process constructs the image into various projection for best matching process. Projection for best matching process is observed from this SRSM can obtain sparse reconstruction coefficients when the gallery image and the probe set are from the same person.

F.Similarities Measure

Similarities measure process can be divided into three major steps: alignment and partitioning, feature extraction, and classification and combination. Existing local matching systems adopt different methods in each of these three steps. Besides comparing overall system performance, we compare the different options in each step.

1) Alignment and Partitioning

The aligned faces are then partitioned into local blocks. The alignment and partition steps are usually related, so we discuss them together. The alignment and partition methods can be divided into three categories. The methods in the first category locate a few local facial components, such as eyes, nose, mouth, and so on. The face is partitioned into these facial components and in the subsequent recognition process the corresponding facial components are compared.

The second category of alignment methods warps the face into a “standard” (shape free) face. Precise regis tration of corresponding pixels is required in the followin g dimensionality reduction process. After warping, shape information can be incorporated into identification by separating shape and appearance features and then comparing them independently. The face is then warped into a “standard” (sha pe free) face to extract shape and appearance (gray-level) features separately.

These two kinds of features are fed into shape and appearance classifiers, and the final classification combin es Misalignment of local patches usually reflects the fact that th e two faces have different global shape, and, therefore, misali gnment can be utilized in the recognition. Additionally, altho ugh warping is designed to transform only the global shape o f the face into a “standard” face, it also defo rms the local facial c omponents.

These local features such as eye corners,mouth corners,nostrils,and eyebrows carry important discriminating information therefore we consider deforming them counterproductive. The third category of appro aches aligns the face into a common coordinate system (instea d of warping it into a standard face) by a similarity transfo rm (translation, rotation and scaling) based on certain detected fiduciallypoint. In many existing face recognition methods f ace images are cropped, keeping only internal components, su ch as eyes, nose, and mouth, and abandoning external features, such as cheek contour and jaw line. Perhaps most researchers assume that internal components and their mutual spatial configuration are the critical constituents of a face, and the external features are too variable.

System architecture

Highly accurate and fast face recognition syste ms can be built using the present hardware and recognition engine. Such a system includes three main software modules as face detection, eye localization,and face matching.Each of t hese performs a two-class classification, i.e., classifying the input into the positive or negative class.

The fundamental learning problem here is to learn a generally nonlinear classifier to classify a learned classifier is a nonlinear mapping from the input sub window to a confidence score.The final classification decision can be done by comparing the score with a confidence threshold.While how to build the face matching engine has been described, here we include how to build the face detector and eye l ocalizer and how to integrate the modules into a system.

LPR method can perform better than NCA in terms of the recognition rate, Compared with LRP, which aims to repulse locality samples from different classes. LRP method with non-neighbor samples can achieve slightly better performance than without these samples, which furt her shows that these samples can still contain some discriminativ e information for seeking the low dimensional feature subspace.

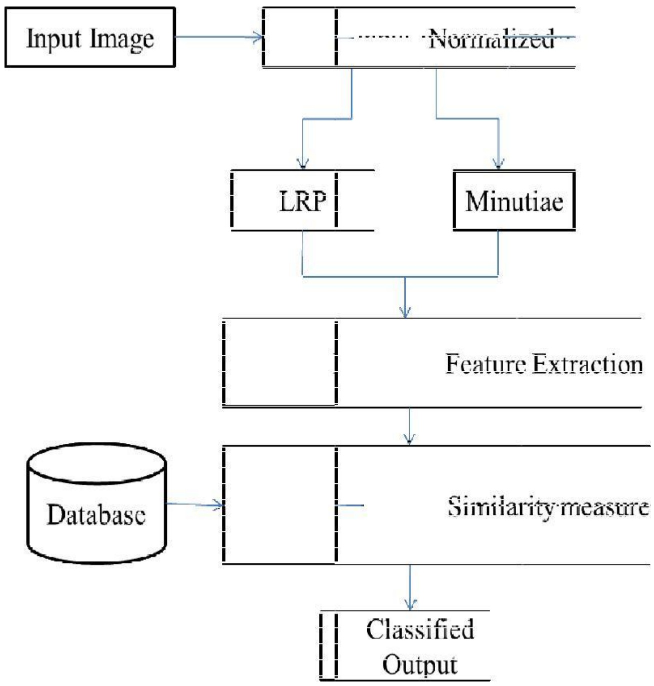

Fig 1: System Architecture

Database

Five publicly available face da tabases used namely AR, CMUPIE, Extended Yale Band F ERET, LFW were used for experiments to demonstrate the e ffectiveness of our proposed approach for controlled image-to se t face recognition.

The FERET database is the most widely used face recognition algorithm.In the FERET database all frontal face pictures are divided into five categories: F ,Fb,Fc,Dup1,and Dup2.The CMU PIE database contains, in total,41 368 images of 68 subjects with 500+ images for each. The face images were captured under varying pose, illum ination, and expression. For each subject, illumination variation, pose of roll/yaw/tilt head rotation, and a moderate variety in expression, constituting a challenging face database for the recognition task.

The CMU PIE (Pose, Illumination and Expression) database contains more than 40,000 facial images of 68 people. The images were acquired across dif ferent poses, under variable illumination conditions, and with different facia l expressions

AR data set consisting different subjects. For each subject13 images in Session were selected. The single image with natural expression and illumination for training other 12 images with illumination changes with expressions and facial disguises for testing.

The Yale face database was constructed at the Yale Center for Computational Vision and Control. It contains 165 gray scale images of 15 individuals. The images with left-light, right light), facial expression (normal, happy, sad, sleepy, surprised, and wink), and with/without glasses.

The LFW face database which was collected under uncontrolled conditions was also used to demonstrate the efficacy of our proposed method for uncontrolled image-to set face recognition experiments.

IV.EXPERIMENTAL RESULTS

In this paper, since there is only one sample per person registered in the gallery set, conventional popular discriminative subspace analysis methods succh as LDA and MFA cannot work with simple sample per person.

Method	AR	CMU PIE	YALE B	FE RET	LFW
PCA	85.2	93.7	44.7	75. 5	18.5
LPP	87.4	94.7	57.9	76. 8	19.9
NPE	87.9	94.2	56.8	77. 5	20.5
LRP	**89.6**	**95.7**	**73.9**	**80. 2**	**21.2**
Minutiae	**89.8**	**96.1**	**62.4**	**80. 2**	**22.1**

Table 1: Compared feature extracted subspace methods

Hence, this paper compared with the other three popular unsupervised face recognition algorithms: PCA, LPP and NPE and implemented these methods and tuned the best parameters for each method for a fair co mparison. LRP demonstrated the effective performance amo ng all the LRP demonstrated the effective performance a mong all the compared feature extracted subspace methods. In the proposedLRP demonstrated the effective perfoormance among all the compared feature extracted subspace methods, In the proposed LRP method for facial feature extraction and compared the recognition performance with four different classifiers: NND-NN, KNNSNN, NN-MV, and proposed SRSM. Minutiae extraction works in three steps search of facial end points, best endpoint solution and ridge reconstruction.

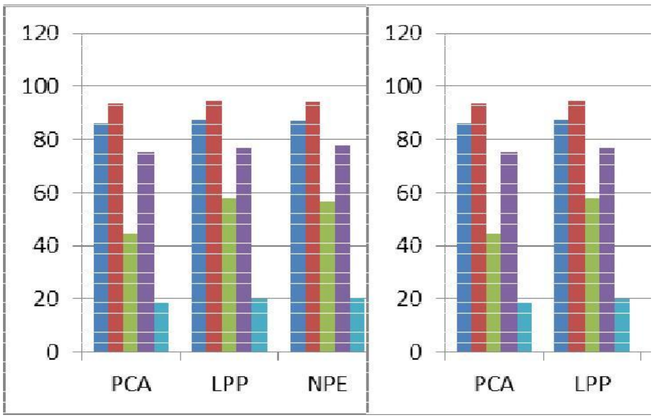

Fig 2(a) Extracted LRP feature Image 1

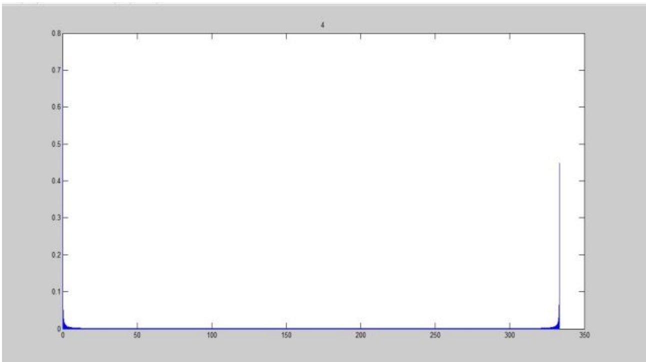

Fig 2(b) Projected feature

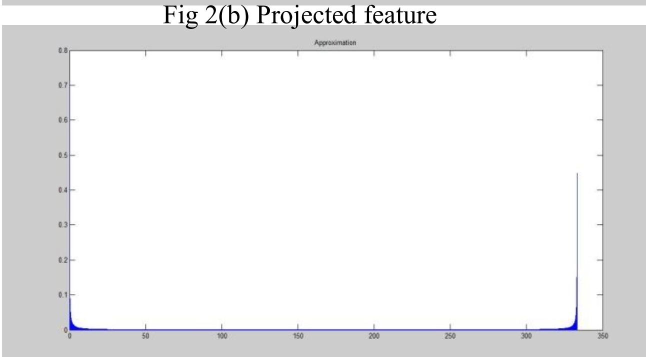

Fig 2(c) LRP extraction

LRP demonstrated the effective performance among all the compared feature extracted su bspace methods. In the proposed LRP method for facial feature extraction and compared the recognition performance with four different classifiers: NND-NN, KNNSNN, NN-MV, and proposed SRSM. Minutiae extraction works in three steps search of facial end points best endpoint solution and ridge reconstruction.

V. CONCLUSION AND FUTURE WORK

Locality repulsion demonstrates that comparing corresponding local regions instead of corresponding local components is an effective way of exploiting variations of facial component configuration (although it may not be what the human vision system does).Locality repulsion does require relatively high resolution images such low resolution pictures are adequatefor human recognition of familiar faces

Comparative analysis of the details of face recognition through localized matching among the three local feature representations, the Eigen (PCA) feature cannot be recommended .Feature selection or weighting with a limited number of training samples remains an interesting and important research topic in machine face recognition. Locality repulsion projection and sparse reconstruction based similarity measure with minutia extraction methods are thinning-based method. In which each ridge is converted to one pixel wide. That is known as skeletonization.

The LRP and minutiae feature extraction method is concerted into modal for the purpose of storage values in the database. The stored values are classified using SVM (support vector matrix).Then the tested images also included with same procedure and further similarity measure is calculated.

In future, work can be explored of the proposed algorithm with effectiveness of face recognition by reducing computational complexity using color transformation of YCBCR. Additionally for effectiveness of proposed system relative databases are added for future extraction of face recognition system.

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