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An Ensemble Method of Global and Local Representation for Face Recognition

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***Abstract*—To aim at the challenge of face recognition to uncontrolled situations, an ensemble method of global and local representation for face recognition is presented in this paper. shearlets transform is firstly employed to decompose a image into subimages. Then directional information is utilized along with conventional scaling and translation parameters, global feature of a face image is extracted by principle component analysis. Thirdly, local feature of a face image is extracted by a deep convolutional neural network. Finally, an ensemble of global and local feature is performed by weighted score. Experimental results on two challenge face databases show that the proposed method achieved higher face recognition accuracy than art-of-the-state methods. Hence, the ensemble of global and local feature is more potential features for the design of efficient face recognition system.**

Keywords- face recognition; Shearlets transform; deep convolution; PCA; ensemble

I. INTRODUCTION

Face recognition (FR) is an active research issue in the area of computer vision and pattern recognition, FR has a wide range of applications, including information security, smart card, law enforcement, video surveillance and access control [1-2]. However, how to extract effective feature representation to describe a face is critical for face recognition. In the past decades, many face algorithms were proposed by researchers. Most of the appearance-based face recognition methods perform some kind of subspace analysis in the image space to extract the relevant feature vectors. The most widely used subspace analysis methods are Principal Component Analysis (PCA) [3], Linear Discriminant Analysis (LDA) [4], and a blind source separation technique, called Independent Component Analysis (ICA) [5]. However, the above methods are only designed for discovering the global features of data, while neglecting the local structure of the data. In fact, local features show certain robustness to local deformations of face images, for example, pose, expression and occlusion. Ojala et al presented one widely influential face descriptor, LBP descriptor, to facilitate rotation invariant analysis of image texture at multiple scales [6]. However, the sparse sampling exploited by LBP operator with large neighbour radius may result in inadequate representation of the face image and more sensitive to the noise. Zhang et al utilized the robustness of Gabor feature to illumination and expression variations and proposed a histogram sequence using local binary pattern descriptor on Gabor magnitude map [7]. Despite the great success of Gabor feature-based local feature FR methods, the Gabor transformations need high computational cost and storage space. When Gabor transformations of a face image need to be implemented at multiple scales and orientations, the many convolutions and Gabor feature maps produce the high time and space complexity during the Gabor feature generation, which prevents its widely utilization in practical applications.

Although multi-resolution techniques like wavelets have been found very useful in analyzing the image contents, it is well known that wavelets have limited ability in expressing directional information. In order to overcome these limitations, a great number of multiscale geometric analysis methods such as curvelets [8] and contourlets [9] owned good characteristic such as locality, multiresolution, directionality and anisotropy, were proposed in the past years, shearlets transform is a newly addition. Multiscale algorithms based on shearlets not only have good localization and compactly support in frequency domain, but also have directionality and anisotropy. With those properties, shearlets can effectively represent image geometrical information of edges, feature points and texture, it has been utilized in image separation [10], image denoising [11], and image edge detection [12]. However, only a few work has been done to solve face recognition and pattern classification problems. For example, Qu proposed a facial expression recognition algorithm based on shearlet transform, which is a new image time-frequency analysis method and provides directionality and anisotropy [13]. However, only low frequency components in shearlet transform are extracted as face image feature in this method, all high frequency components are wholly neglected. In fact, high frequency components include many useful information for face recognition. In addition, Danti proposed a facial texture feature representation based on shearlet transform [14-15], however, this method uses mean and covariance of shearlet transform coefficients as feature representation of a face image, which leads to cost computational complex and low face recognition rate. Borgi proposed a sparse coding augmented approach based on shearlet network, and designed a fusion step by PCA-based method using a refined model of belief function based on the Dempster-Shafer rule in the context of confusion matrices, this method is robust to the problem of a single training sample per subject [16].

Although many face recognition methods have been proposed, most existing face recognition methods utilize hand-crafted features. These methods cannot well extract the nonlinear manifold structure of data points, the resulting features might not be optimally describe face content. Hence, these methods based on hand-crafted features might not obtain satisfactory performance in practice. To solve the shortcoming of above methods based on the hand-crafted features, In recent years, researchers have proposed some face recognition algorithms based deep neural network. Face recognition accuracy has been prompted rapidly using better deep neural network architectures and supervisory methods. Sun proposed a deep network architecture, which is significantly deeper than other deep network architectures for face recognition, and joint face identification-verification supervisory signals are added to the last layer of network [17]. Schroff describes a FaceNet System that directly learns a mapping from face image to a Euclidean space where distances directly correspond to a measure of face similarity [18]. Taigman exploits 3 D face modeling by a piecewise affine transformation to revisit the alignment and representation of face and derive a face representation from a deep neural network [19]. Omkar use a convolutional neural network to learn a face representation on a very large scale training datasets [20]. These methods well learn the nonlinear manifold structure of a face imge and have achieved better results than existing face recognition methods using hand-crafted features.

This paper presents a new method for face recognition which combines shearlets features and deep features. shearlet features describe the shape and appearance information over different scales and directions, and deep represention captures the small structural details of the face image. The remaining part of the paper is organized as follows: In section 2, the shearlets transformation is introduced. Section 3 presents the primary component analysis for shearlets features as global features, and deep features as local features for face recognition. Section 4 presents the strategy of integration of shearlet feature and deep feature. And experiments and results analysis are conducted in section 5, followed by a small discussion, conclusion and future work in section 6.

II. SHEARLETS TRANSFORM

Wavelet representations are optimal for approximating data with pointwise singularities. However, wavelets are not very effective when dealing with multivariate data, wavelets cannot handle equally well distributed singularities such as singularities along curves because wavelets are isotropic objects and generated by isotropically dilating a single or finite set of generators. If distributed discontinuities such as edges of surface boundaries are present in two or higher dimension then wavelets fails to deal with such multivariate data. Curvelets can provide optimally sparse approximations of anisotropic features, but it has two drawbacks. Firstly, the curvelet is not singly generated, it is not derived from the action of countably many operators applied to a single or finite set of generating functions; secondly, its construction involves rotations and these operators do not preserve the digital lattice which prevents a direct transition from the continuum to the digital setting. Later contourlets were proposed by some researchers, but a proper continuum theory is missing in this approach.

Shearlets are derived from a single or finite set of generators and ensures a unified treatment of the continuum and digital world because the shear matrix preserves the integer lattice. It has some unique properties: it has a single or finite set of generating functions, it provides optimally sparse representation for a large class of multidimensional data, it is possible to use compactly supported analyzing functions, it has fast algorithm implementations and it allows a unified treatment of the continuum and digital realms. Shearlets allow optimal encoding of several classes of multivariate data through its ability to sparsely represent anisotropic features and hence Shearlets emerge as the new tool for processing massive and higher dimensional data.

The Shearlets are an affine system which is parameterized by three parameters like- scaling, shear, and translation. The shear parameter can captures the direction of singularities of the face images. The direction of singularities to resolve the wavefront set of distributions can be precisely detected by continuous shearlets transform. The optimally sparse representations for 2-D functions that smooth away from discontinuities along curves can be provided by the discrete Shearlet transform. Another benefit of this approach is that, it provides a multi-resolution analysis similar to the one associated with classical wavelets, which is very useful for the development of fast algorithm implementations.

The idea of the construction of the Shearlet transform using discrete parameters for functions in $L^2(R^2)$ is the choice of a two parameters dilation group, where one parameter ensures the multi-scale property and the other parameter offers a means to test directions. Directions are parameterized by slope rather than angles in shearlets transform, so the structure of the integer grid is preserved by the shear matrix, it is the key that an exact digitization of the continuum domain shearlets is got. Shearlet systems are designed to effectively encode anisotropic features. To achieve optimal sparsity, shearlets are scaled according to scaling law encoded in the scaling matrix **A**, and exhibit directionality by parameterizing slope encoded in the shear matrix **B**, scale matrix **A** and shear matrix **B** is defined as:

$$A = \begin{bmatrix} a & 0 \\ 0 & \sqrt{a} \end{bmatrix} \qquad B = \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix} \tag{1}$$

Hence, Shearlet systems are based on three parameters: $a > 0$ is the scale parameter measuring the resolution level, and $s \in R$ is the shear parameter measuring the directionality, and $t \in R^2$ is the translation parameter measuring the position. This parameter space $R^* \times R \times R^2$ can be given with the group operation, which is defined as:

$$(a,s,t)(a',s',t') = \left(aa', s + s'\sqrt{|a|}, t + BAt'\right) \tag{2}$$

getting the so-called shearlet group B, which can be regarded as a special case of the general affine group. The Continuous Shearlet function arised from the unitary group representation is defined as:

$$\psi_{a,s,t}(x) = a^{-3/4}\psi\left(A^{-1}B^{-1}(x-t)\right) \tag{3}$$

For suitable selections of the Shearlet $\psi \in L^2(R^2)$, the Continuous Shearlet Transform which is given as:

$$SH_f(a,s,t) = < f, \psi_{a,s,t} > \quad (4)$$

where $<,>$ is a linear isometry from $L^2(R^2)$ to $L^2(B)$. Alternatively, rather than defining the shearing parameter s on R, the domain can be restricted to $|s| \leq 1$. This gives rise to the Cone-adapted Continuous Shearlet Transform, which allows an equal treatment of all directions in contrast to a slightly biased treatment by the continuous shearlet transform. By sampling the continuous shearlet transform on an appropriate discrete set of the scaling, shear, and translation parameters, it is possible to obtain a representation or even a parseval representation for $L^2(R)$.To obtain the discrete shearlets, three parameters are sampled as following:

$$a_j = 2^j \left(j \in Z \right), s_{j,k} = k a_j^{1/2} = k 2^{j/2} \left(k \in Z \right), and$$
$$t_{j,k,m} = D_{a_j, s_j, k} \left(m \in Z^2 \right) \quad (5)$$

The mother shearlet function ψ is chosen in a similar fashion as in the continuous case. The tiling of the frequency plane is shown in the figure 1. This system forms a parse value maps for $L^2(R)$, and they are optimally sparse. The discrete Shearlets on the cone, whose tiling of the frequency plane is shown in this figure 2 has the advantage that all directions are treated equally, also each scale is associated with a finite number of shear parameters. Shearlets can be easily constructed by separable and nonseparable generating functions, which is illustrated in figure 3. Shearlets generated from nonseparable functions cover the frequency plane more effectively and provide better frame bounds.

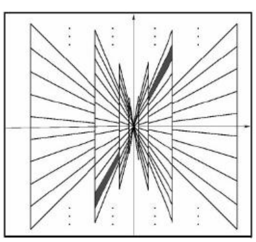

Figure 1 The tiling of frequency plane

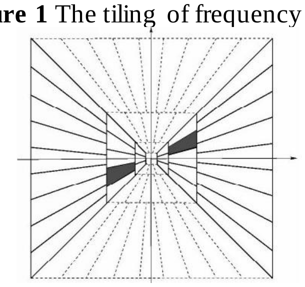

Figure 2 The tiling of the frequency plane induced by discrete Shearlets.

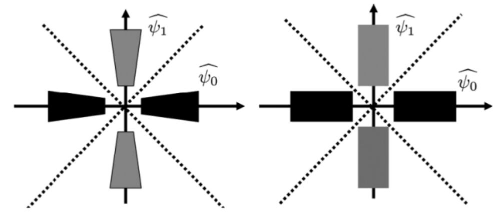

Figure 3 Nonseparable Shearlets (left) and Separable Shearlets (right)

III. GLOBAL FEATURE EXTRACTION

The visual information of a face image can be captured by edges detected not only at different orientations but also multiple scales after a multi-scale decomposition of a face image has been performed by applying the shearlets transform. Generally, a face system includes two stages: training stage and classification stage. In training stage, each face image is decomposed along with horizontal and vertical directions by shearlet transform. Our decomposition is performed upto three levels by varying shearing parameters from $2^{(-j/2)}$ to $2^{(j/2)}$ and scale parameters from zero to two. So we obtain three horizontal cone coefficients and vertical cone coefficients respectively. Then we perform PCA to the magnitude of these coefficients respectively, and then concatenate them into Shearlets features. we consider Shearlets features as the global features of the face image. Same procedure is repeated for all faces of the training database and a feature matrix is constructed from these low dimension Shearlets features. This feature matrix is used as the global features in classification stage to classify the unknown test face image. Shearlet features provide edge responses at a given scale and orientation because shearlet coefficients of large magnitude come from edges, so our Shearlets features are based on the magnitude of shearlet coefficients at different scales and orientations. For clarity, we describe the PCA matrices learning procedure and feature extraction procedure in Algorithms 1 and 2, respectively.

Algorithm 1. Procedure of PCA matrices leaning

Input: T, the training set with N normalized face images.

Output: $W_{s,d}$, PCA matrices.

- Step 1. for each image $I \in T$, shearlet decomposition is performed on I, and we get the shearlet coefficients, then we compute the magnitude of these coefficients $f_{s,d}, s = 1,2,3; d = 1,2$, where s is the scale index and d is the number of directionality on each scale.

- Step 2. Based on $f_{s,d}$, these magnitude vectors are projected to a PCA subspace and then these transformed vectors are used to learn PCA matrices $W_{s,d}, s = 1,2,3; d = 1,2$.

Algorithm 2. Feature extraction using PCA matrices

Input: I, a normalized face image, the learned PCA matrices $W_{s,d}, s = 1,2,3; d = 1,2$.

Output: low-dimensional feature vector F.

- Step 1. For image I , calculate its magnitude of shearlet coefficients $f_{s,d}, s = 1,2,3; d = 1,2$.

- Step 2. Calculate their low-dimensional feature vectors $F_{s,d}, s = 1,2,3; d = 1,2$ respectively using linear transforms: $F_{s,d} = (W_{s,d})^T f_{s,d}$.

- Step 3. Concatenate these low-dimensional feature vectors $F_{s,d}$ to form a face image feature representation F .

IV. DEEP FEATURE EXTRACTION

We use VGG-face pre-trained model for our face feature extractor. The VGG network architecture is shown in Fig.1.

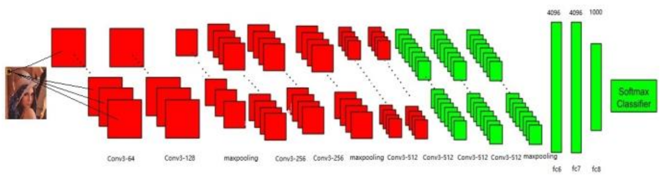

FIGURE IV. THE ARCHITECTURE OF VGG NETWORK

VGG model includes 11 blocks, each is composed of a linear operator followed by one or more non-linearities such as ReLU and max pooling. The first eight such blocks are called as convolutional is a bank of linear filters. The last three blocks are instead called Fully Connected (FC). Though these blocks are the same as a convolutional layer, the size of the filters of these blocks must match the size of the input data, such that each filter can sense data from the entire image. All the convolution layers are followed by a rectification layer (ReLU); The dimensions of first two FC layers output are 4,096 and the dimensions of the last FC layer are 1024. It is critical for the stability of the optimization algorithm that the input to all networks is a face image of size 224×224 with the average face image subtracted.

VGG model use triplet loss as loss function, Optimization is performed by stochastic gradient descent using mini-batches. The model is regularized using dropout and weight decay. The weights of the filters in the CNN were initialised by random sampling from a Gaussian distribution with zero mean and 10^2 standard deviation. Biases were initialised to zero. The training images were rescaled such that the smaller of width and height was equal to 256. During training, the network is fed with random 224×224 pixel patches cropped from these images. The data was further augmented by flipping the image left to right with 50% probability.

After VGG model is trained on 2.6M face images datasets, we delete the soft-max layer of the model, but other layers of the model retain unchanged. Hence, the model acts as a feature extractor for a face image. For a face image, it is rescaled such that its width and height is equal to 224×224, then it is fed into the model to extract face representation(1024 dimensions) for face recognition.

V. ENSEMBLE OF GLOBAL AND LOCAL FEATURE

Shearlets feature and deep feature provide the complementary information to distinguish different human faces. To improve face recognition accuracy, we need to integrate the two kinds of features. Denote by F^p and F^g the deep features of a probe face image and a gallery image, respectively, their similarity using Euclidean distance is defined as:

$$S\left(F^p, F^g\right) = \left\|F^p - F^g\right\|_2^2 \quad (6)$$

where $\| \ \|_2^2$ is the Euclidean distance operator.

We can consider $S\left(F^p, F^g\right)$ as local classifier (LC), and then we compute the Euclidean distance of the dimension reduced Shearlets features and treat it as the global classifier (GC). Finally, we use the simple weighted sum to integrate the GC and LC into unified classifier (UC) as follows:

$$UC = w \bullet GC + (1-w) \bullet LC \quad (7)$$

VI. EXPERIMENTAL AND ANALYSIS

In this section, we first discuss parameter settings, and then we evaluate the proposed algorithm on two large scale benchmark datasets: Multi-PIE [21] and FERET [22], which have been widely used to evaluate face recognition algorithms.

A. Parameter settings

There are some parameters in different stages of the proposed algorithm, for example, multi-scale Shearlet transform and features integration. To consistent with other approaches and provide a fair comparison, pre-processing is the same in all the following experiments.

For all the datasets, to minimize the possible misleading results caused by the training data, the results have been averaged over five experiments, all conducted using the same parameters. Before the shearlets decomposition the images are resized to 256×256 .

In this paper, the parameters in multi-scale shearlets transform are the number of scales, the number of orientations. The number of scales is often set to 3, and the number of orientations is often set to 6. when the model is trained, all images will be rescaled into 256×256 , then 224×224 pixel patches cropped from these images are fed into the network. In the stage of fusing, two similarities LC and GC will be averaged by using the weight *w*. If no specific instruction, we fix *w*=0.25.

B. Experimental results and analysis on Multi-PIE

We use large scale Multi-PIE to verify the performance of the proposed algorithm. The training set in this experiment consist of all the 249 subjects in Session 1. In order to make the face recognition more challenging, the probe set consists of four subsets with both illumination and expression variations in Session 1, 2 and 3. The seven frontal images with extreme illuminations {0,1,7,13,14,16,18} and neutral expressions are used for examples in the training set. Four frontal images with illuminations {0,2,7,13} and different expressions are used for examples in the testing set.

(a)

(b)

(c)

(d)

(e)

FIGURE V. A SUBJECT IN MULTI-PIE DATABASE. (A) TRAINING SAMPLES WITH ONLY ILLUMINATION VARIATIONS. (B) TESTING SAMPLES WITH SURPRISE EXPRESSION AND ILLUMINATIONS IN SESSION 2. (C) TESTING SAMPLES WITH SQUINT EXPRESSION AND ILLUMINATIONS IN SESSION 2. (D) AND (E) TESTING SAMPLES WITH SMILE EXPRESSION AND ILLUMINATION VARIATIONS IN SESSION 1 AND SESSION 3, RESPECTIVELY.

In the experiment on Multi-PIE, LBP [6] is also used as baseline method. we compare the proposed method with the state-of-the-art algorithms, such as HGPP [23], LGXP [24], VGG-Face[20]. The face recognition rates are listed in Table I. It is clear to see that LBP has the worst recognition rate. The proposed method has very competitive recognition rates as HGPP, LGXP and VGG-Face.

TABLE I. RECOGNITION RATE (%) COMPARISON ON MULTI-PIE AMONG DIFFERENT ALGORITHMS AND PROPOSED METHOD

Methods				**Multi-PIE**
	Smile-S1	***Smile-S3***	***Surprise-S2***	***Squint-S2***
LBP	97.0	68.6	69.0	76.9
HGPP	99.2	80.2	75.3	83.4
LGXP	99.1	77.9	72.6	83.5
VGG-Face	99.5	95.8	94.5	97.1
Our method	99.7	96.5	95.6	98.0

In this experiment, it can be seen that the proposed method outperforms LBP, HGPP, LGXP and VGG-Face method in all cases except Squint-S2. These results demonstrate that the fusion of different global and local feature sets is of higher discriminant and better generization than only using one kind of feature, it can overcome the affect of the variation of the face expression and position, and it can effectively eliminate the error of lighting variation. There are two reasons: on the one hand, shearlets feature utilize directional information of Shearlets transform, on the other hand, after reduction, the combined feature sets not only describe the global shape of a face image at a wider range of scales, but also characterize the small detail of a face image.

C. Experimental results and analysis on FERET

We tested the proposed method on the FERET face database of fa, fb, fc, dup1 and dup2 images, The fa images are used as gallery images and the fb, fc, dup1 and dup2 images are used as probes. There are 1196 fa images, 1195 fb images, 194 fc images, 722 dup1 images and 234 dup2 images. All subjects (with 1 exception) have exactly one gallery and one probe image. The fa and fb images for a single subject vary only in expression (neutral versus smiling), fc images were taken under different lighting conditions, dup1 images were taken later in time, and dup2 images were taken at least a year after the corresponding gallery images. We use 1002 randomly selected images from the gallery set for training data.

FIGURE VI SOME SAMPLE IMAGES OF FERET DATABASE

In the experiment on FERET, LBP [6] is still used as baseline method. we compare the proposed method with the state-of-the-art algorithms, such as HGPP [23], LGXP [24], VGG-Face [20]. The experimental results are listed in Table III.

From the experimental results in Table II, we can see that the proposed method outperforms LBP, HGPP, LGXP and VGG-Face methods. These results demonstrate again that the information of direction base on shearlets, Gabor transform is very useful, meanwhile, the fusion of different feature sets is of higher discriminant and better generization than LBP, HGPP, LGXP and VGG-Face method.

Meanwhile, in Table III, we can see that several algorithms have different recognition rates in the FERET dataset, all the methods have good recognition rate in the fb probe dataset, these results illuminate that the recognition rates of these algorithms are not affected by the variety of the face expression when the time of the gallery images taken is the same as the time of the probe images taken. The recognition rates of these algorithms except LBP almost remain unchanged for the fc probe dataset, the recognition rate of LBP method clearly decrease for fc probe dataset, which account for that these methods except LBP are insensitive to the difference of the illumination. Although the proposed method use PCA to reduce the dimension of shearlet feature, it has good recognition performance for fc probe dataset, this illustrates shearlets transform can eliminate the affection of variation of illumination.

TABLE II. RECOGNITION RATE (%) COMPARISON ON FERET AMONG DIFFERENT ALGORITHMS AND PROPOSED METHOD

Methods	FERET			
	fb	***fc***	***Dup1***	***Dup2***
LBP	97.0	79.0	66.0	64.0
HGPP	97.5	99.4	79.6	77.8
LGXP	99.1	99.0	93.6	93.0
VGG-Face	99.7	99.8	97.6	97.2
Our method	99.8	99.9	98.3	98.0

The recognition rates of all the algorithms clearly decrease for the dup1 and dup2 datasets, but the worse results were got for the dup2 dataset. It is visible the longer time of the face image taken, the more variation of face image is owing to individual natural aging, especially local difference of face, it should lead to more affection for face recognition. In the dup2 dataset, the recognition rate of LBP is 64.0 percent, the recognition rates of HGPP is 77.8, the recognition rates of other methods are more than 93.0 percent, the recognition rate of the proposed method is 98.0 percent, the integration of global and local feature sets could improve in average 34.0 percent than LBP, in average 21.2 percent than HGPP, respectively. this illustrates that the combination of the global and local feature with directional information are robust for the individual aging

VII. CONCLUSIONS

In this paper, we investigated a novel face recognition method using shearlets feature reduced by PCA as global feature and deep representation as local feature, we found that the ensemble of global and local feature is more potential features for the design of efficient face recognition system. Meanwhile, the unique features of shearlets transform is optimally sparse representation for a large class of multidimensional data and unified treatment of the continuum and digital world, which might be helpful for improved recognition rate. The experimental results obtained on two different datasets are encouraging: we show that using the combined features based on decision fusion can be got good performance. The performance can be further improved by applying other strategy of features fusion and better classifiers.

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