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Performance Analysis of Hierarchical Face Recognition

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Abstract:
Information jointly contained in image space, scale and orientation domains can provide rich important clues not seen in either individual of these domains. The position, spatial frequency and orientation selectivity properties are believed to have an important role in visual perception. This paper proposes a novel face representation and recognition approach by exploring information jointly in image space, scale and orientation domains. Specifically, the face image is first decomposed into different scale and orientation responses by convolving multiscale and multiorientation Gabor filters. Second, local binary pattern analysis is used to describe the neighboring relationship not only in image space, but also in different scale and orientation responses. This way, information from different domains is explored to give a good face representation for recognition. Neural Networks provide significant benefits in face recognition. They are actively being used for such advantages as locating previously undetected patterns, controlling devices based on feedback, and detecting characteristics in face recognition. It improves the level of accuracy compared with existing face recognition methods.

1. Introduction

In face analysis, a key issue is the descriptor of the face appearance. The efficiency of the descriptor depends on its representation and the ease of extracting it from the face. Ideally, a good descriptor should have a high variance among classes (between different persons or expressions), but little or no variation within classes (same person or expression in different conditions). These descriptors are used in several areas, such as, facial expression and face recognition. There are two common approaches to extract facial features: geometric-feature-based and appearance-based methods.

The former, encodes the shape and locations of different facial components, which are combined into a feature vector that represents the face. An instance of these methods are the graph-based methods, which use several facial components to create a representation of the face and process it. Moreover, the Local-Global Graph algorithm is an interesting approach that uses Voronoi tessellation and Delaunay graphs to segment local features and builds a graph for face and expression recognition. These features are mixed into a local graph, and then the algorithm creates an skeleton (global graph) by interrelating the local graphs to represent the topology of the face. Furthermore, facial features are widely used in expression recognition, as the pioneer work of Ekman and Friesen identifying six basic emotions produced a system to categorize the expressions, known as Facial Action Coding System, and later it was simplified to the Emotional Facial Action Coding System. However, the geometric-feature-based methods usually require accurate and reliable facial feature detection and tracking, which is difficult to accommodate in many situations. The appearance-based methods, use image filters, either on the whole-face, to create holistic features, or some specific face-region, to create local features, to extract the appearance changes in the face image. The performance of the appearance-based methods is excellent in constrained environment but their performance degrade in environmental variation.

2. Literature Review

In the literature, in this paper propose that as one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past few years. There are at least two reasons for this trend; the first is the wide range of commercial and law enforcement applications and the second is the availability of feasible technologies after 30 years of research. In addition, the problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology. The strong need for user- friendly systems that can secure our assets and protect our privacy without losing our identity in a sea of numbers is obvious.

In this paper proposed that in order to solve the problem of face recognition in natural illumination, a new face recognition algorithm using Eigen face-Fisher Linear Discriminate (EFLD) and Dynamic Fuzzy Neural Network (DFNN) is proposed in this paper, which can solve the dimension of feature, and deal with the problem of classification easily. This paper used EFLD model to extract the face feature, which will be considered as the input of the DFNN. And the DFNN is implemented as a classifier to solve the problem of classification. The proposed algorithm has been tested on ORL face database. The experiment results show that the algorithm reduces the dimension of face feature and finds a best subspace for the classification of human face. And by optimizing the architecture of dynamic fuzzy neural network reduces the classification error and raises the correct recognition rate. So the algorithm works well on face database with different expression, pose and illumination.

In this paper proposed that a novel face recognition method which exploits both global and local discriminative features. In this method, global features are extracted from the whole face images by keeping the low- frequency coefficients of Fourier transform, which we believe encodes the holistic facial information, such as facial contour. For local feature extraction, Gabor wavelets are exploited considering their biological relevance. After that, Fisher's linear discriminated (FLD) is separately applied to the global Fourier features and each local patch of Gabor features. Thus, multiple FLD classifiers are obtained, each embodying different facial evidences for face recognition. Finally, all these classifiers are combined to form a hierarchical ensemble classifier. We evaluate the proposed method using two large-scale face databases: FERET and FRGC version 2.0. Experiments show that the results of our method are impressively better than the best known results with the same evaluation protocol.

Dynamic texture is an extension of texture to the temporal domain. Description and recognition of dynamic textures have attracted growing attention. In this paper, a novel approach for recognizing dynamic textures is proposed and its simplifications and extensions to facial image analysis are also considered. First, the textures are modeled with volume local binary patterns (VLBP), which are an extension of the LBP operator widely used in ordinary texture analysis, combining motion and appearance. To make the approach computationally simple and easy to extend, only the co-occurrences on three orthogonal planes (LBP-TOP) are then considered. A block-based method is also proposed to deal with specific dynamic events, such as facial expressions, in which local information and its spatial locations should also be taken into account. In experiments with two dynamic texture databases, DynTex and MIT, both the VLBP and LBP-TOP clearly outperformed the earlier approaches. The proposed block-based method was evaluated with the Cohn- Kanade facial expression database with excellent results. Advantages of our approach include local processing, robustness to monotonic gray- scale changes and simple computation

In this paper proposed that a novel face representation and recognition method based on local Gabor textons. Textons, defined as a vocabulary of local characteristic features, are a good description of the perceptually distinguishable micro-structures on objects. In this paper, we incorporate the advantages of Gabor feature and textons strategy together to form Gabor textons. And for the specificity of face images, we propose local Gabor textons (LGT) to portray faces more precisely and anciently. The local Gabor textons histogram sequence is then utilized for face representation and a weighted histogram sequence matching mechanism is introduced for face recognition. Preliminary experiments on FERET database show promising results of the proposed method.

In this paper proposed that a novel object descriptor, histogram of Gabor phase pattern (HGPP), is proposed for robust face recognition. In HGPP, the quadrant-bit codes are first extracted from faces based on the Gabor transformation. Global Gabor phase pattern (GGPP) and local Gabor phase pattern (LGPP) are then proposed to encode the phase variations. GGPP captures the variations derived from the orientation changing of Gabor wavelet at a given scale (frequency), while LGPP encodes the local neighborhood variations by using a novel local XOR pattern (LXP) operator.

They are both divided into the no overlapping rectangular regions, from which spatial histograms are extracted and concatenated into an extended histogram feature to represent the original image.

Finally, the recognition is performed by using the nearest-neighbor classifier with histogram intersection as the similarity measurement. The features of HGPP lie in two aspects:

- HGPP can describe the general face images robustly without the training procedure;
- HGPP encodes the Gabor phase information, while most previous face recognition methods exploit the Gabor magnitude information.

In addition, Fisher separation criterion is further used to improve the performance of HGPP by weighing the sub regions of the image according to their discriminative powers. The proposed methods are successfully applied to face recognition and the experiment results on the large-scale FERET and CAS-PEAL databases show that the proposed algorithms significantly outperform other well-known systems in terms of recognition rate.

In this paper proposed that a novel and efficient facial image representation based on local binary pattern (LBP) texture features. The face image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. The performance of the proposed method is assessed in the face recognition problem under different challenges.

In this paper proposed that Face recognition system based on the only single classifier considering the restricted information cannot guarantee the generality and superiority of performances in a real situation. To challenge such problems, we propose the hybrid Fourier features extracted from different frequency bands and multiple face models.

The hybrid Fourier feature comprises three different Fourier domains; merged real and imaginary components, Fourier spectrum and phase angle. When deriving Fourier features from three Fourier domains, we define three different frequency bandwidths, so that additional complementary features can be obtained.

After this, they are individually classified by Linear Discriminated Analysis. This approach makes possible analyzing a face image from the various viewpoints to recognize identities. Moreover, we propose multiple face models based on different eye positions with a same image size, and it contributes to increasing the performance of the proposed system. They evaluated this proposed system using the Face Recognition Grand Challenge (FRGC) experimental protocols known as the largest data sets available.

Experimental results on FRGC version
2.0 data sets has proven that the proposed method shows better verification rates than the baseline of FRGC on 2D frontal face images under various situations such as illumination changes, expression changes, and time elapses.

In this paper proposed that an appearance based face recognition method called the Laplacian face approach. By using Locality Preserving Projections (LPP), the face images are mapped into a face subspace for analysis. Different from Principal Component Analysis (PCA) and Linear Discriminated Analysis (LDA) which effectively see only the Euclidean structure of face space, LPP finds an embedding that preserves local information, and obtains a face subspace that best detects the essential face manifold structure.

The Laplacian faces are the optimal linear approximations to the eigen functions of the Laplace Beltrami operator on the face manifold. In this way, the unwanted variations resulting from changes in lighting, facial expression, and pose may be eliminated or reduced. Theoretical analysis shows that PCA, LDA and LPP can be obtained from different graph models. We compare the proposed Laplacian face approach with Eigen face and Fisher face methods on three different face datasets. Experimental results suggest that the proposed Laplacian face approach provides a better representation and achieves lower error rates in face recognition.

In this paper proposed that For researchers in face recognition area have been representing and recognizing faces based on subspace discriminated analysis or statistical learning. Nevertheless, these approaches are always suffering from the generalizability problem. Novel non-statistics based face representation approach, Local Gabor Binary Pattern Histogram Sequence (LGBPHS), in which training procedure is unnecessary to construct the face model, so that the generalizability problem is naturally avoided. In this approach, a face image is modeled as a "histogram sequence" by concatenating the histograms of all the local regions of all the local Gabor magnitude binary pattern maps.

For recognition, histogram intersection is used to measure the similarity of different LGBPHSes and the nearest neighborhood is exploited for final classification. Additionally, we have further proposed to assign different weights for each histogram piece when measuring two LGBPHSes. Our experimental results on AR and FERET face database show the validity of the proposed approach especially for partially occluded face images, and more impressively, we have achieved the best result on FERET face database.

In this paper proposed that recently there has been a lot of interest in geometrically motivated approaches to data analysis in high dimensional spaces. They consider the case where data is drawn from sampling a probability distribution that has support on or near a sub manifold of Euclidean space. Novel subspace learning algorithm called Neighborhood Preserving Embedding (NPE). Different from Principal Component Analysis (PCA) which aims at preserving the global Euclidean structure, NPE aims at preserving the local neighborhood structure on the data manifold. Therefore, NPE is less sensitive to outliers than PCA. Also, comparing to the recently proposed manifold learning algorithms such as Isomap and Locally Linear Embedding, NPE is defined everywhere, rather than only on the training data points. Furthermore, NPE may be conducted in the original space or in the reproducing kernel Hilbert space into which data points are mapped. This gives rise to kernel NPE.

3. Proposed Method Module Description

Four basic frame works are proposed. They are

- Gabor filtering or Transformation,
- Feature Extraction,
- Neural Network Training and Classification

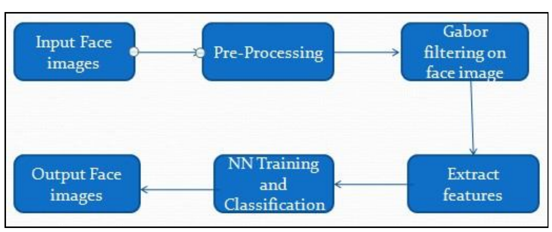

Figure 1: Flowchart representation

4. Gabor Filtering or Transformation

Gabor filters, which exhibit desirable characteristics of spatial locality and orientation selectively and are optimally localized in the space and frequency domains, have been extensively and successfully used in face recognition. The Gabor kernels used are defined as follows:

$$\boxed{\psi_{\mu,\nu} = \frac{k_{\mu,\nu}^2}{\sigma^2} \exp\left(-\frac{k_{\mu,\nu}^2 z^2}{2\sigma^2}\right) \times \left[\exp(ik_{\mu,\nu}z) - \exp\left(-\frac{\sigma^2}{2}\right)\right]} \quad \text{---(1)}$$

where and define μ & υ the orientation and scale of the Gabor kernels, respectively,z=(x,y), and the wave vector is defined as,

$$k_{\mu,v} = k_v e^{i\phi_\mu} \text{-------------}(2)$$

The Gabor kernels are all self- similar since they can be generated from one filter, the mother wavelet, by scaling and rotating via the wave vector. Hence, a band of Gabor filters is generated by a set of various scales and rotations. In this paper, we use Gabor kernels at five scales and eight orientations with the parameter to derive the Gabor representation by convolving face images with corresponding Gabor kernels. For every image pixel we have totally 40 Gabor magnitude and phase coefficients, respectively, that is to say, we can obtain 40 Gabor magnitude and 40 Gabor phase faces from a single input face image.

5. Local Binary Pattern (LBP)

The local binary pattern operator is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. Through its recent extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in many empirical studies. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its invariance against monotonic gray level changes. Another equally important is its computational simplicity, which makes it possible to analyze images in challenging real- time settings. The LBP method and its variants have already been used in a large number of applications all over the world.

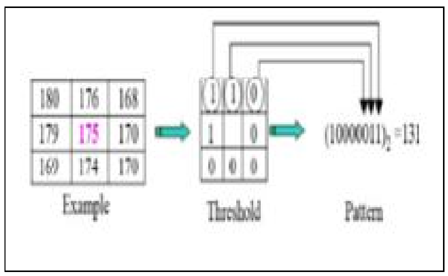

Figure 2: Basic LBP operator

6. Gabor Volume Based LBP on Three Orthogonal Planes (GV-LBP-TOP)

LBP is introduced as a powerful local descriptor for micro features of images. The basic LBP operator labels the pixels of an image by thresholding the 3*3-neighborhood of each pixel with the center value and considering the result as a binary number (or called LBP codes). An illustration of the basic LBP operator is shown in Fig 3. Recently, the combination of Gabor and LBP has been demonstrated to be an effective way for face recognition.

In this paper, proposes to explore discriminative information by modeling the neighboring relationship not only in spatial domain, but also among different frequency and orientation properties. Particularly, for a face image, the derived Gabor faces are assembled by the order of different scales and orientations to form a third-order volume as illustrated in Figure.

where the three axes X, Y, T denote the different rows, columns of face image and different types of Gabor filters, respectively.

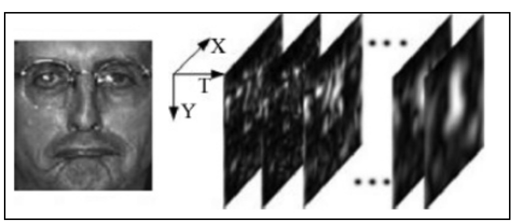

Figure 3: Face image and its corresponding third-order Gabor volume

It can be seen that the existing methods essentially applied LBP or LXP operator on XY plane. It is natural and possible to conduct the similar analysis on XT and YT planes to explore more sufficient and discriminative information for face representation. GV-LBP- TOP is originated from this idea.

It first applies LBP analysis on the three orthogonal planes (XY, XT, and YT) of Gabor face volume and then combines the description codes together to represent faces. Fig. illustrates examples of Gabor magnitude and phase faces and their corresponding GV-LBP codes on XY, XT, and YT planes. It is clear to see that the codes from three planes are different and, hence, may supply complementary information helpful for face recognition. After that, three histograms corresponding to GV-LBP-XY, GV-LBP-XT, and GV-LBP-YT codes are computed as,

$$H_j(l) = \sum_{x,y} I(f_j(x,y) = l), \quad l = 0,1,\ldots,L_j - 1 \qquad \text{-- (3)}$$

in which is an indication function of a Boolean condition and expresses the GV-LBP codes in jth plane (: XY; 1: XT; 2: YT), and is the number of the jth GV-LBP code.
The GV-LBP-TOP histogram is finally derived by concatenating these three histograms to represent the face that incorporates the spatial information and the co- occurrence statistics in Gabor frequency and orientation domains and, thus, is more effective for face representation and recognition.

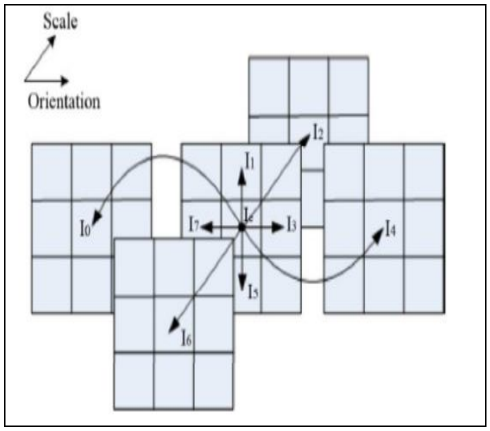

Figure 4: Formulation of E-GV-LBP

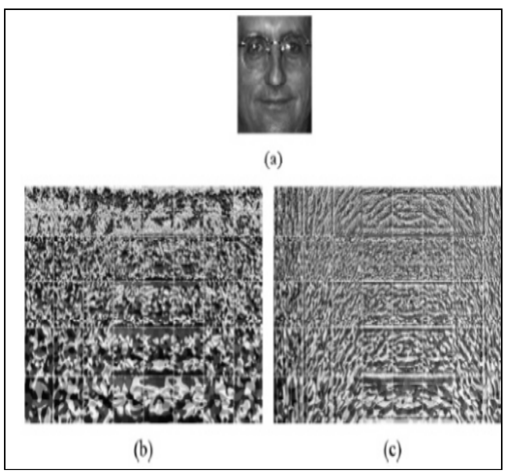

Figure 5

a. One face image and its E-GV-*LBP results on*
b. Gabor magnitude faces and
c. Gabor phase faces

7. Simulation Results

Test Images

Input Image Vs. LDN Image

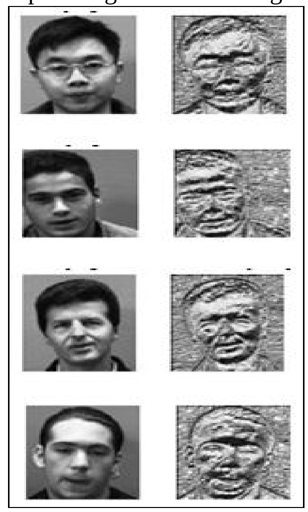

Figure 6: Test Image *Figure 7: Test Image to LDN image*

Performance Comparison of face recognition in terms of elapsed time

Image Sequences	PCA	Neural Networks
Image1	0.20	0.1
Image2	0.061	0.020
Image3	0.074	0.008
Image4	0.055	0.0091

Performance Parameter	PCA	Neural Networks
Classification Accuracy	50%	98%

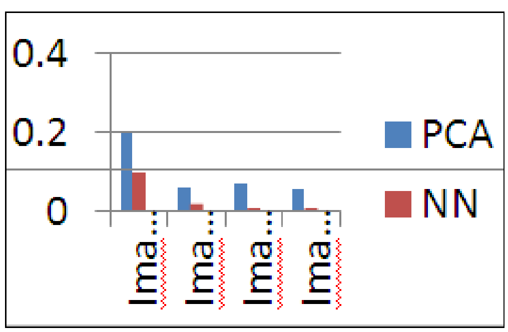

Figure 8: Performance Analysis Graph

8. References

1. Adin Ramirez Rivera, Jorge Rojas Castillo,and Oksam Chae "Local Directional Number Pattern for Face Analysis:Face and Expression Recognition" IEEE transactions on image processing, vol. 22, no. 5, May 2013.
2. W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," ACM Comput. Surv., vol. 35, no. 4, pp. 399–458, Dec. 2003.
3. S. Z. Li, A. K. Jain, Y. L. Tian, T. Kanade, and J. F. Cohn, "Facial expression analysis," in Handbook of Face Recognition. New York: Springer-Verlag, 2005, pp. 247–275.
4. H. Hong, H. Neven, and C. von der Malsburg, "Online facial expression recognition based on personalized galleries," in Proc. 3rd IEEE Int. Conf. Autom. Face Gesture Recognit., Apr. 1998, pp. 354–359.

5. I. Kotsia and I. Pitas, “Facial expression recognition in image sequences using geometric deformation features and support vector machines,”IEEE Trans. Image Process., vol. 16, no. 1, pp. 172–187, Jan. 2007.
6. N. G. Bourbakis and P. Kakumanu, “Skin- based face detection-extraction and recognition of facial expressions,” in Applied Pattern Recognition. New York: Springer-Verlag, 2008, pp. 3–27.
7. N. Bourbakis, A. Esposito, and D. Kavraki, “Extracting and associating meta-features for understanding people’s emotional behaviour: Face and speech,” Cognit. Comput., vol. 3, no. 3, pp. 436–448, 2011.
8. P. Kakumanu and N. Bourbakis, “A local- global graph approach for facial expression recognition,” in Proc. 18th IEEE Int. Conf. Tools Artif.Intell., Nov. 2006, pp. 685–692.
9. A. Cheddad, D. Mohamad, and A. A. Manaf, “Exploiting voronoi diagram properties in face segmentation and feature extraction,” Pattern Recognit., vol. 41, no. 12, pp. 3842–3859, 2008
10. X. Xie and K.-M. Lam, “Facial expression recognition based on shape and texture,” Pattern Recognit., vol. 42, no. 5, pp. 1003–1011, 2009.
11. P. Ekman, Emotions Revealed: Recognizing Faces and Feelings to Improve Communication and Emotional Life. New York: Times Books,2003.
12. P. Ekman and W. Friesen, Facial Action Coding System: A Technique for the Measurement of Facial Movement. Palo Alto, CA: Consulting Psychologists Press, 1978.
13. W. V. Friesen and P. Ekman, “EMFACS- 7: Emotional facial action coding system,” unpublished, 1983.
14. C. Shan, S. Gong, and P. W. McOwan, “Facial expression recognition based on local binary patterns: A comprehensive study,” Image Vis. Comput., vol. 27, no. 6, pp. 803–816, 2009.
15. Y. L. Tian, “Evaluation of face resolution for expression analysis,” in Proc. Conf. Comput. Vis. Pattern Recognit. Workshop, Jun. 2004, p. 82.
16. M. Pantic and L. J. M. Rothkrantz, “Automatic analysis of facial expressions: The state of the art,” IEEE Trans. Pattern Anal. Mach.Intell., vol. 22, no. 12, pp. 1424–1445, Dec. 2000.
17. M. Turk and A. Pentland, “Eigenfaces for recognition,” J. Cogni Neurosci., vol. 3, no. 1, pp. 71–86, 1991.
18. P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, “Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 711–720, Jul. 1997.
19. J. Yang, D. Zhang, A. F. Frangi, and J. Y. Yang, “Two-dimensional PCA: A new approach to appearance-based face representation and recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 1, pp. 131–137, Jan. 2004