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Face Recognition by Exploring Information Jointly in Space, Scale and Orientation

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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.

I. INTRODUCTION

In face analysis, a key issue is the descriptor of the face appearance [1], [2]. 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 [3]. The former [4], [5] 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 [6]–[10], which use several facial components to create a representation of the face and process it. Moreover, the Local-Global Graph algorithm [6]–[8] 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 [11] identifying six basic emotions produced a system to categorize the expressions, known as Facial Action Coding System [12], and later it was simplified to the Emotional Facial Action Coding System [13]. 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 [14], [15] 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 [16].

II.LITERATURE REVIEW

In the literature, there are many methods for the holistic class, such as, Eigenfaces [17] and Fisherfaces [18], which are built on Principal Component Analysis (PCA) [17]; the more recent 2D PCA [19], and Linear Discriminant Analysis [20] are also examples of holistic methods. Although these methods have been studied widely, local descriptors have gained attention because of their robustness to illumination and pose variations. Heisele *et al.* showed the validity of the component-based methods, and how they outperform holistic methods [21]. The local-feature methods compute the descriptor from parts of the face, and then gather the information into one descriptor. Among these methods are Local Features Analysis [22], Gabor features [23], Elastic Bunch Graph Matching [24], and Local Binary Pattern (LBP) [14], [25]. The last one is an extension of the LBP feature, that was originally designed for texture description [26], applied to face recognition. LBP achieved better performance than previous methods, thus it gained popularity, and was studied extensively. Newer methods tried to overcome the shortcomings of LBP, like Local Ternary Pattern (LTP) [27], and Local Directional Pattern (LDiP) [28]–[30]. The last method encodes the directional information in the neighborhood, instead of the intensity. Also, Zhang *et al.* [31], [32] explored the use of higher order local derivatives (LDeP) to produce better results than LBP. Both methods use other information, instead of intensity, to overcome noise and illumination variation problems. However, these methods still suffer in non-monotonic illumination variation, random noise, and changes in pose, age, and expression conditions. Although some methods, like Gradientfaces [33], have a high discrimination power under illumination variation, they still have low recognition capabilities for expression and age variation conditions. However, some methods explored different features, such as, infrared [34], near infrared [32], and phase information [35], [36], to overcome the illumination problem while maintaining the performance under difficult conditions.

III.PROPOSED METHOD MODULE DESCRIPTION

Four basic frame works are proposed. They are i)Gabor filtering or Transformation

ii)Feature Extraction

iii)Neural Network Training and Classification

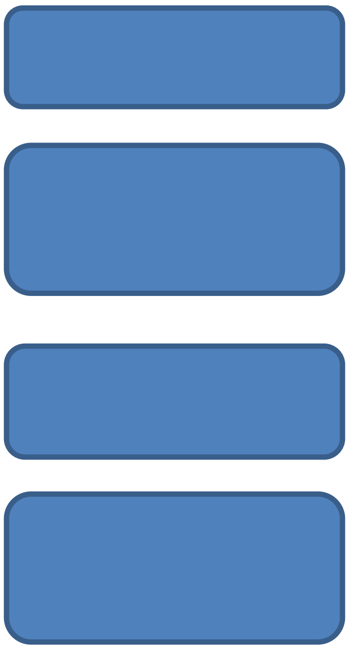


Fig.5.1Flow chart representation of proposed work

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:

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

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

$$k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$$

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.

THE 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.

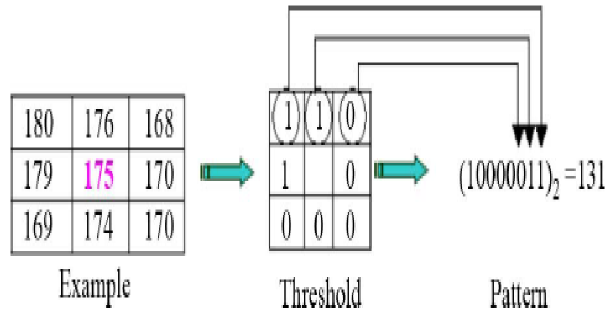


Fig 5.2Basic LBP operator

GABOR VOLUME BASED LBP ON THREE ORTHOGONAL PLANES (GV-LBP-TOP)

LBP is introduced as a powerful local descriptor for microfeatures 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.5.2. 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 Fig.5.3, where the three axes X, Y, T denote the different rows, columns of face image and different types of Gabor filters, respectively.

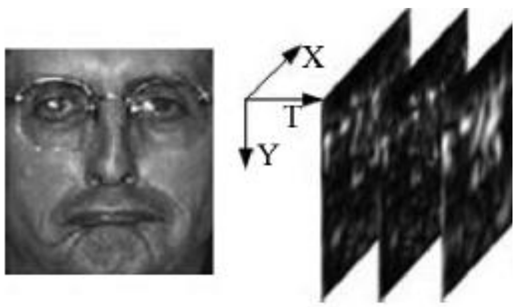


Fig 5.3 Face image and its corresponding third-order Gabor volume.

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. 3.2 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

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

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.

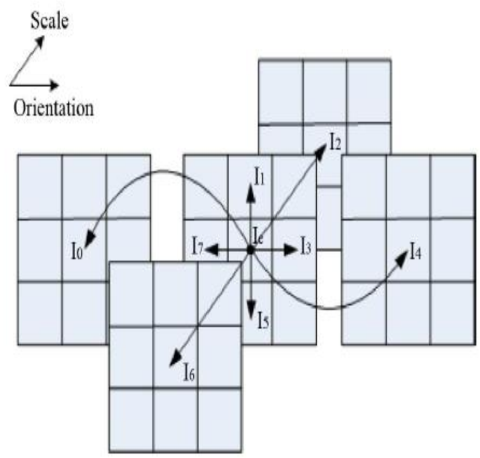


Fig 5.4 Formulation of E-GV-LBP.

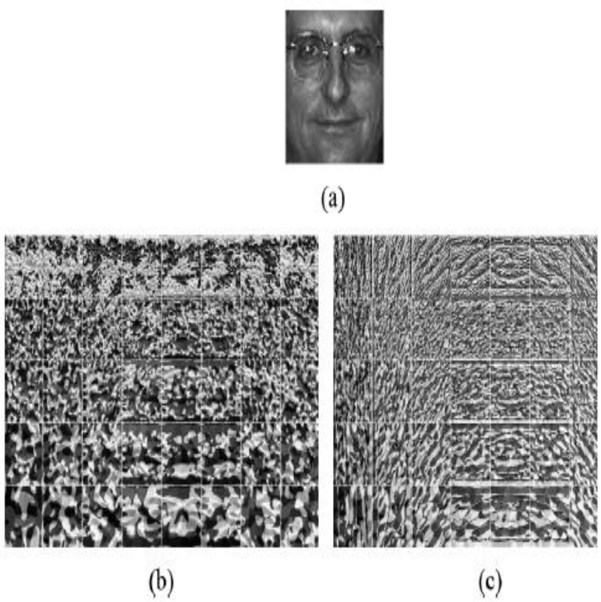
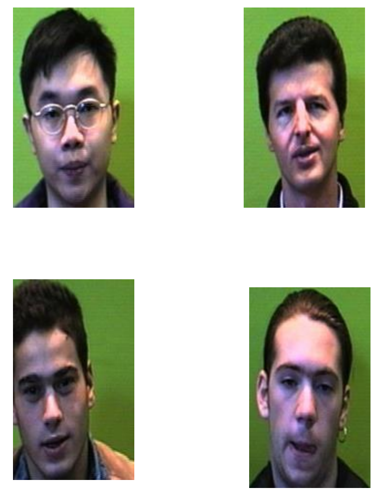
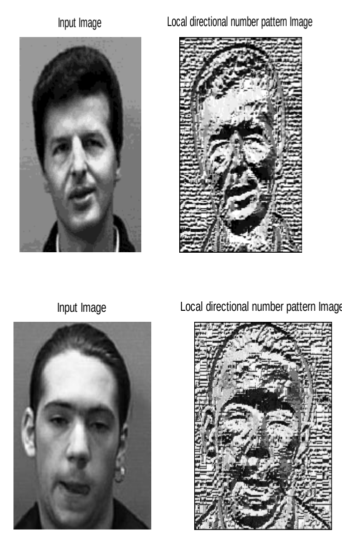


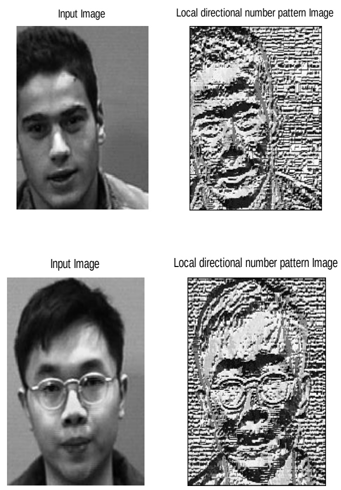
Fig 5.5. (a) One face image and its E-GV-LBP results on
(b) Gabor magnitude faces and
(c) Gabor phase faces

IV.SIMULATION RESULTS

Test Images:





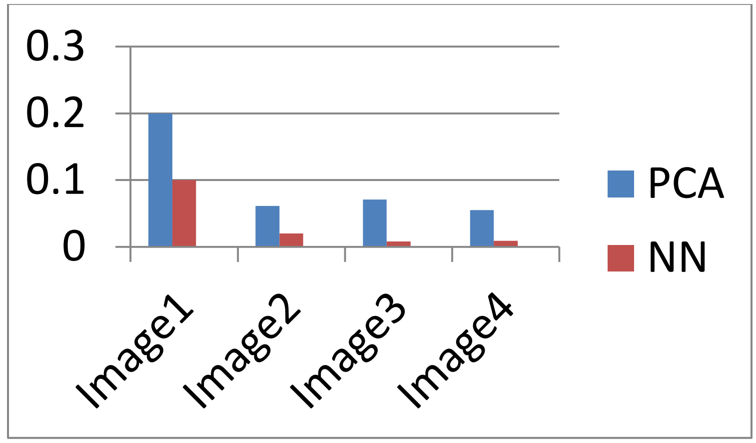


Performance Comparison of face recognition in terms of elapsed time:

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%

Performance Analysis Graph:



V.REFERENCES

[1] R. Chellappa, C. Wilson, and S. Sirohey, "Human and machine recognition of faces: A survey," *Proc. IEEE*, vol. 83, no. 5, pp. 705–741, May 1995.

[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.

[20] K. Etemad and R. Chellappa, "Discriminant analysis for recognition of human face images," *J. Opt. Soc. Amer. A*, vol. 14, no. 8, pp. 1724–1733, 1997.

[21] B. Heisele, T. Serre, and T. Poggio, "A component-based framework for face detection and identification," *Int. J. Comput. Vis.*, vol. 74, pp. 167–181, Aug. 2007.

[22] P. Penev and J. Atick, "Local feature analysis: A general statistical theory for object representation," *Netw., Comput. Neural Syst.*, vol. 7, no. 3, pp. 477–500, 1996.

[23] D. Gabor, "Theory of communication," *J. Inst. Electr. Eng. III, Radio Commun. Eng.*, vol. 93, no. 26, pp. 429–457, Nov. 1946.

[24] L. Wiskott, J.-M. Fellous, N. Kuiger, and C. von der Malsburg, "Face recognition by elastic bunch graph matching," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 7, pp. 775–779, Jul. 1997.

[25] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[26] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on

feature distributions," *Pattern Recognit.*, vol. 29, no. 1, pp. 51–59, Jan. 1996.
[27] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," *IEEE Trans. Image Process.*, vol. 19, no. 6, pp. 1635–1650, Jun. 2010.
[28] T. Jabid, M. H. Kabir, and O. Chae, "Local directional pattern (LDP) for face recognition," in *Proc. IEEE Int. Conf. Consum. Electron.*, Mar. 2010, pp. 329–330.
[29] T. Jabid, M. H. Kabir, and O. Chae, "Robust facial expression recognition based on local directional pattern," *ETRI J.*, vol. 32, no. 5, pp. 784–794, 2010.
[30] M. Kabir, T. Jabid, and O. Chae, "A local directional pattern variance (LDPv) based face descriptor for human facial expression recognition," in *Proc. 7th IEEE Int. Conf. Adv. Video Signal Based Surveill.*, Sep. 2010, pp. 526–532.