

# Local Gradient Order Pattern for Face Representation and Recognition

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**Abstract**—LBP is an effective descriptor for face recognition. LBP encodes the ordinal relationship between the neighborhood samplings and the central one to obtain robust face representation. However, additional information like the difference among neighboring pixels, which may be helpful for face recognition, is ignored. On the other hand, gradient information which enhances the edge response and suppresses the external noise like illumination variation, is usually useful for face recognition. In this paper, we propose a novel face descriptor, namely local gradient order pattern (LGOP), taking into account the ordinal relationship of gradient responses in local region to obtain robust face representation. After pattern encoding, a 2-D histogram is consequently adopted to calculate the occurrence frequency of different patterns and multi-scale histogram features are extracted to represent the face image. We further adopt whitened principal component analysis (WPCA) to reduce the feature dimensionality and improve the computational efficiency. Extensive experiments on FERET, CAS-PEAL and LFW validates the effectiveness of LGOP for both constrained and unconstrained face recognition problems.

## I. INTRODUCTION

Face recognition has been widely deployed in real applications [13], such as access control, face tagging in social network, and human-machine interaction etc. With the development of face recognition in last decades, face recognition under controlled scenarios has been well solved. However, its performance in unconstrained environment is still a great challenge. The large expression, illumination, occlusion and pose variations are still critical issues affecting the face recognition performance.

To address the face appearance variation problem, one possible and straightforward way is to extract face representation robust to these variations. Actually, how to extract effective face representation is always a critical problem in face recognition field. In early years of face recognition study, the face image pixels are firstly vectorized and the dimensionality reduction methods are then applied to the high-dimensional space to find an effective essential subspace to discriminate face images. These methods are usually called holistic features, in which principal component analysis (PCA) [24], linear discriminant analysis (LDA) [2] based subspace learning methods are representative works.

Later, researchers find that the holistic methods are sensitive to local variations such as expression, lighting and occlusion because of its holistic characteristic. Therefore, a number of local features which describe the local texture

variations rather than the entire face attract more attention. Gabor [17], [11], LBP [1], LGBP [32], TPLBP, FPLBP [28], POEM [26], LPQ [25] etc. are all popular local descriptors, which achieve great success in face recognition field.

Recently, the attribute based face representation have been also proposed to address unconstrained face recognition problem. In [10], a number of attribute and simile classifiers are constructed to realize a semantic face representation. In [3], Tom and Pete (SVM) classifiers are trained to extract sufficient discriminative features, each of which is learned to differentiate person pairs independently. These learned attribute based face representations are discriminative and robust to face variations and achieve state-of-the-art performance on challenging LFW database [9].

In this paper, we propose a simple yet effective face representation for face recognition. As we know, LBP models the ordinal information between the central point and its neighbors. However, the ordinal relationship among neighboring pixels are ignored. We find that the ordinal information among these neighboring pixels is also useful for face recognition. In fact, the local intensity order pattern (LIOP) [27] has been proposed and achieved good performance in object recognition, indicating the effectiveness of the ordinal information among neighboring pixels. On the other hand, the gradient information is robust to face recognition. It enhances the useful information like edge texture and meanwhile suppresses the external noise effect like illumination variation. Therefore, in this work, we incorporate the advantage of the ordinal information of neighboring pixels and the gradient response and propose a novel face descriptor, namely local gradient order pattern (LGBP). For each face image, two gradient response images are firstly generated by computing gradient responses along horizontal and vertical directions. Secondly, the neighboring pixels are sampled from these two response images, respectively. The LGOP is finally encoded according to the order of the sampled pixel values from the two gradient response images. We evaluate the proposed LGOP on three face databases, including constrained and unconstrained settings and indicate that LGOP is an effective and competitive face descriptor for robust face representation and recognition.

The remainder of this paper is organized as follows. Section II briefly reviews local intensity order pattern. Section III details the local gradient order pattern and its extraction process. Section IV introduces the two metrics used in this work. Experiments on FERET, CAS-PEAL-R1 and LFW face databases are illustrated in Section VI and in Section VII, we

conclude the paper.

## II. LOCAL INTENSITY ORDER PATTERN

Local intensity order pattern (LIOP) [27] takes into account the order of values of elements in data vector and maps the data vector to its permutation space (also namely LIOP code space). Given a  $d$ -dimensional vector  $P = [p_1, p_2, \dots, p_d] \in R^d$  and a possible permutation set  $\Pi$  of integers  $\{1, 2, \dots, d\}$ , the mapping from  $P$  to  $\Pi$  is defined as follows. Firstly, we sort the elements in  $P$  in a non-descending order. That is,  $p_{i_1} \leq p_{i_2} \leq \dots \leq p_{i_d}$ . Secondly, the subscript list  $i_1, i_2, \dots, i_d$  is considered as the mapping result in set  $\Pi$  and is denoted using a unique scalar (LIOP code). To avoid ambiguity,  $p_s \leq p_t$  is defined as if and only if (1)  $p_s < p_t$  or (2)  $p_s = p_t$  and  $s < t$ . It is obvious that for a  $d$ -dimensional vector, there are  $d!$  possible permutations. Fig. 1 illustrates an example of LIOP encoding.

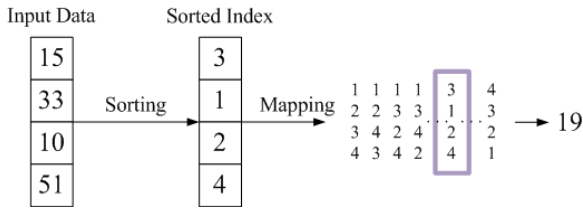


Fig. 1. The LIOP encoding process.

## III. LOCAL GRADIENT ORDER PATTERN

Gradient information has been shown to be important and effective to represent objects. Popular descriptors like SIFT [18] and HOG [6] extract local gradient information to describe the texture of objects robustly. Different from LIOP, in this work, we propose to exploit the ordinal relationship of gradient response rather than image intensity, so that more discriminative and robust representation could be achieved. In particular, two 1st-order gradient responses (horizontal and vertical) are considered and a novel local gradient order pattern (LGOP) is proposed to describe face images. Fig. 2 shows the process of LGOP extraction.

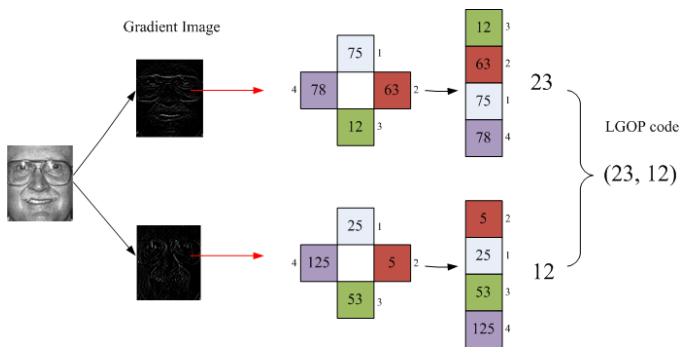


Fig. 2. The LGOP pair encoding process.

Given a face image, the horizontal and vertical gradient responses are firstly computed. After that, for each pixel, its neighbors are sampled and sorted in non-descending order. The order index is then mapped to its permutation space as in LIOP to form the LGOP codes. Finally, the LGOP codes

generated from horizontal and vertical gradient responses are combined to form the LGOP pair. As shown in Fig. 2, in which four neighborhood samplings are considered, the original values of four samples from two gradient response images are (75, 63, 12, 78) and (25, 5, 53, 125). After sorting in non-descending order, their order indices are (3,2,1,4) and (2,1,3,4), respectively. The LGOP pair is finally encoded as (23,12) because (3,2,1,4) and (2,1,3,4) are the 23th and 12th vectors in permutation set.

### A. Block based Analysis

In this work, we adopted block based LGOP computation. As adopted in [16], for each neighborhood sampling, the mean value of local block centered at the point is used instead of the single pixel value. In this way, the resulted LGOP is more stable and hence is more robust to noise effect. Fig. 3 shows an example of block based pattern comparison. The scale of block size  $S$  is a parameter that can be adjusted in implementation.

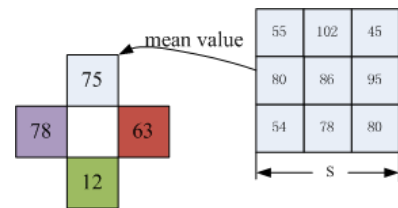


Fig. 3. The example of block based LGOP analysis.

### B. Multi-scale Two dimensional Histogram Feature

To preserve the spatial information in face image, we extract a number of two-dimensional histogram features that describe the occurrence frequency of LGOP pairs in local regions. For each local histogram extraction, we divide the local region (cell) into 4 blocks and extract the histogram feature from these 4 blocks and the whole cell, respectively. These 5 histogram based features are then concatenated. Fig. 4 shows the histogram extraction process. In this way, histogram features at multi-scales are extracted, which are expected to be complementary to enhance the representative ability of face images. These two-dimensional histogram features extracted from different local regions are finally concatenated to represent the whole face. The size of local region  $R$  is another parameter needs be determined in our algorithm.

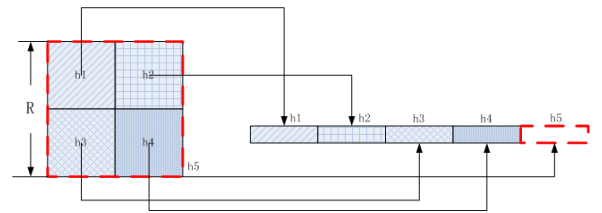


Fig. 4. The multi-scale histogram feature extraction process.

### C. Neighborhood sampling method

Considering the computational cost, four neighbors are sampled in LGOP encoding. To exploit more discriminative and complementary information, we adopt two different sampling methods (shown in Fig. 5) and fuse the recognition results at the score level.

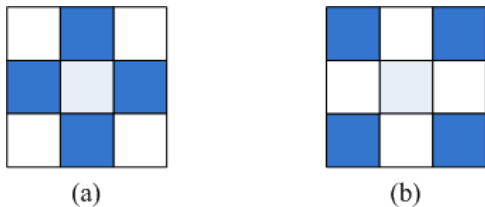


Fig. 5. Two neighborhood sampling ways used in LGOP. In each way, four neighbors (the blue blocks) around the central one are sampled and compared.

#### IV. DISSIMILARITY MEASURE

After feature extraction, the next step is to measure the dissimilarity between two feature vectors. One straightforward way is to use histogram intersection metric to compute the dissimilarity of the histogram based features. In this work, we adopt weighted histogram intersection to differentiate the importance of the different face regions to enhance the face recognition performance. Given two histogram based features  $H^a = [h_1^a, h_2^a, \dots, h_d^a]$  and  $H^b = [h_1^b, h_2^b, \dots, h_d^b]$ , where  $d$  is the number of local patches, the weighted histogram intersection is defined as

$$D(H^a, H^b) = \sum_i w_i \sum_k \min(h_i^a(k), h_i^b(k)) \quad (1)$$

where  $h(k)$  is the  $k$ -th bin value of histogram  $h$ . The weight  $w_i$  is determined using Fisher criterion as in [32], representing the discriminative ability of different face regions. The distinct regions for face recognition like eyebrow, eye, nose etc. usually have higher weights than other regions like mouth and cheek.

The original histogram based feature is usually of high dimension. Directly comparing different features is not a very efficient way. Dimensionality reduction is an effective way to reduce the computational cost and meanwhile improve the discriminative ability. In many real application, there is only one face image per person available. Many supervised methods like LDA cannot be applied directly in this case. In this work, we adopt the unsupervised whitened PCA [26], which balances the importance of different feature dimensions by normalizing the energy of each dimension in the reduced feature space. After WPCA reduction, the cosine metric (Eq. 2) is adopted to compute the dissimilarity of two reduced feature vectors.

$$d_{\cos}(x_1, x_2) = \frac{x_1^T x_2}{\sqrt{x_1^T x_1 x_2^T x_2}} \quad (2)$$

In the following experiments, Eq. 1 and Eq. 2 is applied to features with/without WPCA reduction, respectively.

#### V. RELATED FACE DESCRIPTORS

Ordinal information is always an important clue for face recognition. In [15], authors apply multi-pole ordinal filters to face representation. The ordinal relationship between local regions are measured. Later, Liao et al. [14] combine several ordinal measures and propose structured ordinal feature (SOF) for face representation. SOF integrates the advantage of ordinal measure and LBP and achieves robust face recognition performance in constrained case. Chai et al. [4] propose Gabor ordinal measures, which extract the ordinal measure on Gabor

responses. By incorporating the robustness of Gabor and ordinal measures, it is robust to variations like expression, lighting, occlusion etc. However, the computational complexity is also greatly increased. In these works, the ordinal relationship is measured by comparing the values of two regions and being thresholded into binary value. Local salient patterns (LSP) [5] is the most related work to this paper. In LSP, the ordinal information among neighborhood samplings are exploited. The order of the pixels with the maximum and minimum values are encoded. This work takes into account the order information among all neighborhood samplings and is expected to achieve more discriminative face representation.

#### VI. EXPERIMENTS

We compare LGOP with many existing face descriptors including LBP, LGBP, LGT, LVP, LQP etc. The performance of LGOP and LIOP is also compared. Three popular face databases (FERET, CAS-PEAL-R1, LFW) are used to evaluate the performance of various methods in both constrained and unconstrained scenarios.

##### A. Data Description

The FERET [22] database is one of the largest publicly available databases. The training set contains 1002 images. In test phase, there are one gallery set containing 1196 images from 1196 subjects, and four probe sets (fb, fc, dup I and dup II) including expression, illumination and aging variations.

The CAS-PEAL-R1 database [8] is a large-scale Chinese face database, which provides face images with different variations, including pose, expression, accessory and lighting. In this experiment, we follow the standard testing protocols. The gallery set includes 1040 images from 1040 persons. For probe sets, we use the expression, lighting, accessory subsets, which contains 1570, 2243, 2285 images, respectively.

Labeled Faces in the Wild (LFW) [9] is a database collected from the web for studying the problem of unconstrained face recognition. There are 13,233 images from 5,749 different persons, with large pose, occlusion, expression variations. In testing phase, researchers are suggested to report performance as 10-fold cross validation using splits which are randomly generated and provided by the organizers.

For FERET and CAS-PEAL, all the images are cropped to  $150 \times 130$  size according to the provided eye coordinates. For LFW, we use the aligned images (LFW-a) [29] and crop the images with the size of  $150 \times 130$  from the original images. Fig. 6 shows some cropped examples from these three face databases.

##### B. Parameter Specification

In this work, we extract the histogram based features from a evenly distributed local regions in face image. Fig. 7 illustrates the distribution of centers of local regions over the face image. There are in total  $11 \times 9 = 99$  local regions. For the proposed LGOP, there are two critical parameters, i.e., the scale of block size  $S$  (shown in Fig. 3) and the size of local region  $R$  in histogram based feature extraction (shown in Fig. 4). In the following, we examine the effects of these two parameters

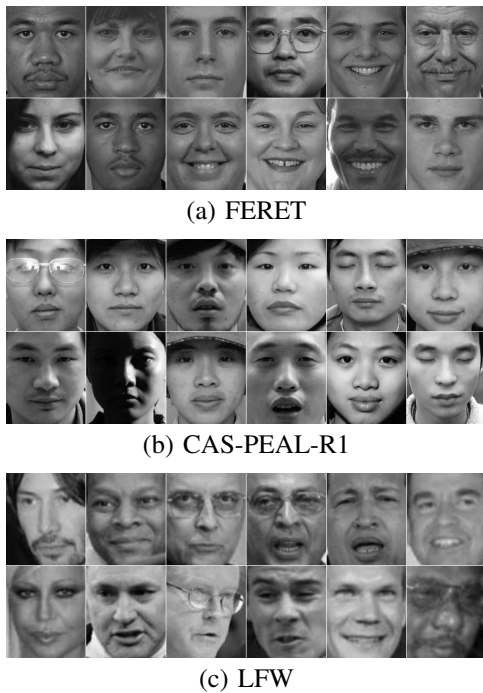


Fig. 6. Cropped face examples from FERET (a), CAS-PEAL (b) and LFW (c) databases.



Fig. 7. The distribution of centers of local regions in histogram based feature extraction.

on face recognition performance following four probe sets on FERET database.

First, we fix the histogram size  $R$  to 21 and examine the face recognition performance (Fig. 8(a)) with respect to different block sizes ( $S = 9, 15, 21, 27$ ) in LGOP encoding. As expected, small scale is relatively sensitive to noise effect and large scale may lose some fine information useful for face recognition. From the results, we can see that the best face recognition performance is achieved when  $S$  is set to 15.

Next, by setting  $S$  to 15, Fig 8(b) shows the face recognition performance with different local region sizes  $R$  in histogram feature extraction. The face recognition performance is relatively stable when  $R$  is selected from 21, 23, 25. In the following experiments, we simply set  $R$  to 23.

### C. LGOP vs. LIOP

Table I lists the recognition results of LGOP and LIOP on four probe sets. For fair comparison, both LIOP and LGOP adopts the same sampling method shown in Fig. 5(a). The radius of neighborhood sampling and the local region size of histogram based feature extraction are set the same for LIOP

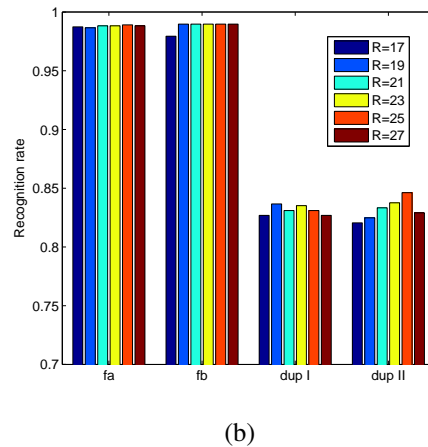
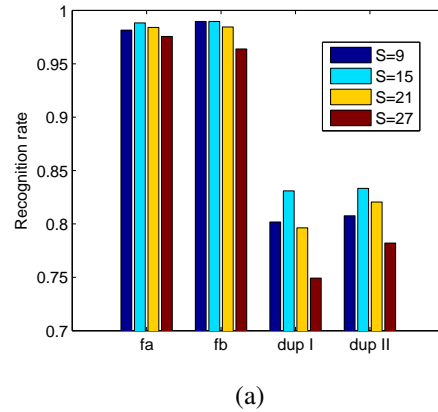


Fig. 8. Face recognition performance with respect to different parameters ((a) scale of block size  $S$  and (b) the size of local histogram region  $R$ ).

and LGOP. It is shown that the original LIOP is not able to represent face images sufficiently. Comparatively, LGOP, which incorporates the gradient responses and the ordinal information in neighborhood region can exploit the identity-preserving features successfully. LGOP outperforms LIOP on all four probe sets of FERET database.

TABLE I. RECOGNITION RESULTS (%) OF LGOP AND LIOP ON FERET DATABASE.

Methods	fb	fc	dup I	dup II
LIOP [27]	97.0	79.0	66.0	64.0
LGOP	98.0	97.0	74.0	71.0

### D. Comparison with state-of-the-art methods

Table II lists the face recognition performance of LGOP compared with popular face descriptors. The “whole” face recognition rate is reported by combining all probe images from four probe sets. With weighted histogram intersection, LGOP outperforms the classical LBP, LGBP, HGPP etc. in most cases. It enhances the recently proposed POEM, LQP by 3.5% and 11.3% in terms of the whole face recognition. Compared with LSP, LGOP achieves the similar recognition performance on fb and fc probe sets and improves LSP by 4.3% and 7.3%, respectively on dup I and dup II probe sets. It

indicates that LGOP successfully extracts more discriminative clues for face recognition. The learning based descriptors like DT-LBP, DLBP and DFD achieve slightly better recognition results than LGOP in some cases. It motivates us that it is possible to incorporate the learning based way to improve the performance of LGOP in future. With WPCA and cosine metric, LGOP improves its robustness to face appearance variations, especially to aging effect. With WPCA, LGOP outperforms POEM and LQP by 0.4% and 2.4% in terms of the whole face recognition rate, validating its effectiveness for face representation and recognition.

TABLE II. COMPARISON RECOGNITION RATE (%) ON FERET DATABASE.

Methods	fb	fc	dup I	dup II	whole
LBP [1]	97.0	79.0	66.0	64.0	82.6
LGBP [32]	98.0	97.0	74.0	71.0	87.8
LVP [21]	97.0	70.0	66.0	50.0	80.5
LGT [11]	97.0	90.0	71.0	67.0	85.4
HGPP [31]	97.5	99.5	79.5	77.8	90.1
LLGP [30]	99.0	99.0	80.0	78.0	91.0
DT-LBP [19]	99.0	100.0	84.0	80.0	92.5
DLBP [20]	99.0	99.0	86.0	85.0	93.6
POEM [26]	97.6	95.0	77.6	76.2	89.1
LQP [25]	99.2	69.6	65.8	48.3	81.3
LSP [5]	98.1	99.0	79.2	76.5	90.2
DFD [12]	99.2	98.5	85.0	82.9	93.1
POEM+WPCA [26]	99.6	99.5	88.8	85.0	94.8
LQP+WPCA [25]	99.8	94.3	85.5	78.6	92.8
DFD+WPCA [12]	99.4	100.0	91.8	92.3	96.4
LGOP	98.8	99.0	83.5	83.8	92.6
LGOP+WPCA	99.2	99.5	89.5	88.5	95.2

### E. CAS-PEAL-R1

We further examine the robustness of different methods to expression, accessory and lighting variations on CAS-PEAL-R1 database. We also report the “whole” face recognition performance by combining all the probe images. Table III lists the recognition rates of various methods. From the results, we can see that the Gabor related descriptors like LGBP, LLGP, HGPP achieve better performance in the case of lighting variation. For the expression and accessory variations, the learning based descriptors (DT-LBP, DLBP, DFD) and proposed LGOP performs better than others. Overall, with WPCA and cosine metric, LGOP achieves the highest accuracy in terms of whole face recognition rate, indicating the superiority of LGOP for face representation.

TABLE III. COMPARISON RECOGNITION RATE (%) ON CAS-PEAL-R1 DATABASE.

Methods	expression	accessory	lighting	whole
LGBP [32]	95.0	87.0	51.0	75.7
LVP [21]	96.0	86.0	33.0	68.9
HGPP [31]	96.8	92.5	62.9	82.7
LLGP [30]	98.0	92.0	55.0	79.8
DT-LBP [19]	98.0	92.0	41.0	74.6
DLBP [20]	99.0	92.0	41.0	74.8
DFD [12]	99.3	94.4	59.0	82.5
DFD+WPCA [12]	99.0	96.9	63.9	85.2
LGOP	98.7	93.2	47.6	77.7
LGOP+WPCA	99.6	96.8	69.9	87.6

### F. Unconstrained Face Recognition

We test on the “View 2” set of LFW, which consists of 10 folds of 300 positive and 300 negative image pairs randomly

selected from the original image set. In this experiment, all the methods are tested in an unsupervised way. That is, no class information is used in training phase. The mean classification with its standard error of the 10-fold cross-validation is reported.

The LGOP is compared with popular descriptors including LBP, Gabor, SIFT, LARK, POEM, LQP, DFD etc. Table IV lists the mean accuracy of different methods on LFW database and the corresponding ROC curves are illustrated in Fig. 9. Without whitened PCA, the proposed LGOP achieves higher recognition accuracy than LBP, Gabor, SIFT, POEM, LQP etc, indicating the superiority of LGOP over these descriptors. The LGOP performs slightly worse than hybrid descriptor which is a combination of LBP, TPLBP, FPLBP and Gabor with two different metrics. The learning based DFD achieves the best recognition results in this case. With whitened PCA, the face recognition performance of LGOP is significantly improved. It outperforms POEM and DFD by 2.6% and 1.3%, respectively. Overall, the comparison results show that LGOP is an effective and competitive descriptor for unconstrained face recognition, which is very promising in real application.

TABLE IV. MEAN RECOGNITION ACCURACY (%) FOR DIFFERENT DESCRIPTORS ON LFW DATABASE.

Descriptor	Accuracy
LBP [7]	69.45±0.5
Gabor [7]	68.47±0.7
SIFT [7]	64.10±0.6
Hybrid descriptor [28]	78.47±0.5
LARK [23]	72.23±0.5
POEM [26]	75.22±0.7
LQP [25]	75.30±0.8
DFD [12]	80.02±0.5
POEM+WPCA [26]	82.71±0.6
LQP+WPCA [25]	86.20±0.5
DFD+WPCA [12]	84.02±0.4
LGOP	77.03±0.5
LGOP+WPCA	85.38±0.4

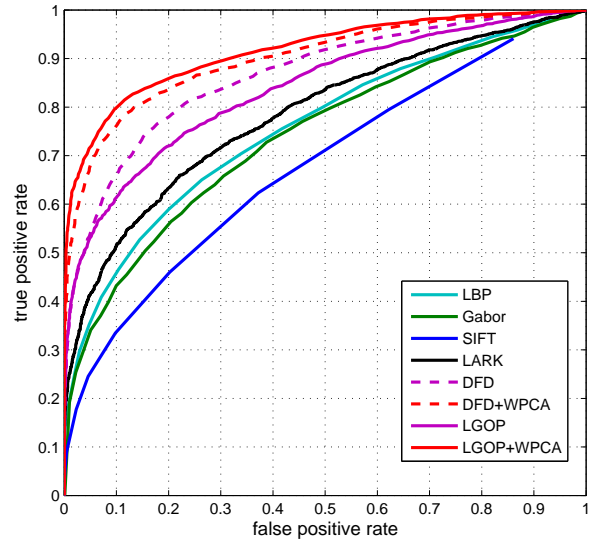


Fig. 9. ROC curves over View 2 on LFW database. The results of LBP, Gabor, SIFT, LARK and DFD are cited from the website (<http://vis-www.cs.umass.edu/lfw/results.html>) directly.

## VII. CONCLUSIONS

In this paper, we propose a local gradient order pattern (LGOP) for face representation and recognition. By incorporating advantage of gradient responses and ordinal information in local neighborhood region, a discriminative and robust face descriptor is derived. Different pattern samplings and multi-scale histogram feature extraction are adopted to exploit the useful facial information sufficiently. The whitened PCA is further adopted to reduce the dimension of LGOP feature and enhance the discriminative ability. Experiments on constrained and unconstrained face recognition scenarios indicate that LGOP is comparable with state-of-the-art descriptors and is an effective descriptor for real face recognition.

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