Fast multi-scale local phase quantization histogram for face recognition

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Multi-scale local phase quantization (MLPQ) is an effective face descriptor for face recognition. In previous work, MLPQ is computed by using Short-term Fourier Transformation (SFT) in local regions and the high-dimension histogram based features are extracted for face representation. This paper tries to improve MLPQ based face recognition in terms of accuracy and efficiency. It has two main contributions. First, a fast MLPQ extraction algorithm is proposed which produces the same results with original MLPQ method but is about three times faster than the original one in practice. Second, a novel feature selection method combining Adaboost and regression is proposed to select the most discriminative and suitable features for the subsequent subspace learning. Experiments on FERET and FRGC ver 2.0 databases validate the effectiveness and efficiency of the proposed method.

1. Introduction

Face recognition has attracted much attention due to its potential value for applications and its theoretical challenges. In real world, the face images are usually affected by different expressions, poses, occlusions and illuminations, and the differences of face images from the same person could be larger than those from different ones. Therefore, how to extract robust and discriminant features which make the intra-person faces compact and enlarge the margin among different persons has become a critical and difficult problem in face recognition.

Up to now, many face representation approaches have been introduced, including subspace based holistic features and local appearance features (Zhao et al., 2003; Li et al., 2005). Typical holistic features include the well known principal component analysis (PCA) (Turk and Pentland, 1991), linear discriminate analysis (LDA) (Belhumeur et al., 1997), independent component analysis (ICA) (Comon, 1994) etc. PCA provides an optimal linear transformation from the original image space to an orthogonal eigenspace with reduced dimensionality in sense of the least mean square reconstruction error. LDA seeks a linear transformation by maximizing the ratio of between-class variance and within-class variance. ICA is a generalization of PCA, which is sensitive to the high-order correlation among the image pixels. Recently, Yan et al. (2007) re-interpret the subspace learning from the view of graph embedding so that various methods, such as PCA, LDA, LPP (He et al., 2005) etc. can all be interpreted under this framework.

Local appearance features, as opposed to holistic features like PCA and LDA, have certain advantages. They are more stable to local changes such as illumination, expression and inaccurate alignment. Gabor (Liu and Wechsler, 2002; Lei et al., 2007) and local binary patterns (LBP) (Ahonen et al., 2006) are two representative features. Gabor wavelets capture the local structure corresponding to specific spatial frequency (scale), spatial locality, and selective orientation. It has been demonstrated to be discriminative and robust to illumination and expression changes. Local binary patterns (LBP) which describes the neighboring changes around the central point, is a simple yet effective way to represent faces. It is invariant to monotone transformation and is robust to illumination changes to some extent. The combination of Gabor and LBP further improves the face recognition performance. A lot of work has been proposed in this branch (Zhang et al., 2005, 2006, 2007; Lei et al., 2011).

Recently, local phase quantization (LPQ) is proposed for texture analysis (Ojansivu and Heikkilä, 2008) and applied to blurred face recognition (Ahonen et al., 2008). In LPQ, complex responses at four low frequency points are encoded and local co-concurrence is extracted for face representation. Further, the extension of LPQ, namely multi-scale LPQ (MLPQ) (Chan et al., 2009) is proposed to describe the face image more sufficiently and completely. After extracting local histogram features based on MLPQ responses with various scales, linear or kernel discriminant analysis is applied to determine the most discriminant subspace to be classified. Besides its blur invariance, MLPQ is also proved to be an effective descriptor for general face recognition under various conditions. Note that LPQ is actually a special case of MLPQ with one scale. However, MLPQ is computed by using Short-term Fourier Transformation (SFT) in local regions and the high-dimension histogram based features are extracted for face representation. This paper tries to improve MLPQ based face recognition in terms of accuracy and efficiency. It has two main contributions. First, a fast MLPQ extraction algorithm is proposed which produces the same results with original MLPQ method but is about three times faster than the original one in practice. Second, a novel feature selection method combining Adaboost and regression is proposed to select the most discriminative and suitable features for the subsequent subspace learning. Experiments on FERET and FRGC ver 2.0 databases validate the effectiveness and efficiency of the proposed method.

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compared with LBP, one of the main problems for MLQP is its relatively higher computation burden in feature extraction. Moreover, the dimension of original histogram feature for MLQP is high and it is inefficient to conduct discriminant analysis or compute similarity on it directly. All of these limit the widespread application of MLQP.

In this paper, we propose a fast MLQP algorithm based on integral images. The proposed fast MLQP algorithm produces the same results as the original one but is three times faster than the original version in our experimental testing. Moreover, in order to get an effective face recognition model, we take the dimensionality increasing technique (Liu, 2006). A high-dimension and over-complete MLQP feature set is first extracted. Appropriate feature selection and subspace learning is further utilized to reduce the dimension of feature and improve the discriminative power of the model. Different from the existing method (Shan et al., 2005; Li et al., 2007; Lei et al., 2011), we propose an Adaboost and regression based feature selection to select most discriminative and proper features for subspace learning. In testing phase, only the selected features need to be extracted so that the computational cost is greatly reduced.

It is worthwhile to highlight two main contributions of this paper (yellow parts in Fig. 1).

1. A fast MLQP extraction algorithm is proposed.
2. A suitable feature selection method for subspace learning by using Adaboost and regression is presented.

The rest of this paper is organized as follows. Section 2 briefly reviews the definition of MLQP. Section 3 details the fast MLQP extraction process. Section 4 describes the feature selection and transformation method. Experimental results and analysis are demonstrated in Section 5 and in Section 6, we conclude the paper.

2. Multi-scale local phase quantization

The principle of LPQ is to extract the phase information in frequency domain which is robust to blur variation. In the frequency domain, the blurring process can be represented as $G = F \cdot H$, where $G$ is the Fourier transform of the blurred image, $F$ the original image, and $H$ the point spread function (PSF). The magnitude and phase components therefore satisfy

$$|G| = |F| \cdot |H|$$
$$\angle G = \angle F + \angle H$$

(1)

Assuming that the PSF is centrally symmetric, the transform $H$ will be real valued and the phase of $H$ will equal 0 or $\pi$. In the LPQ method, it is assumed that in the very-low frequency band, the value of $H$ is positive with $\angle H = 0$, so the phase information of $G$ and $F$ is the same and therefore a blur invariant representation can be obtained from the phase.

In a realization, the local frequency can be computed using a Short-term Fourier Transform (SFT) on local $M \times M$ neighborhoods $N_k$ at each pixel position $x$ of the image $f(x)$ defined by

$$f(u, x) = \sum_{y \in N_k} f(x - y)e^{-j2\pi uy'}$$

(2)

In Ahonen et al. (2008), the responses at four frequency points $u = [u_0, u_1, u_2, u_3]$ are extracted, where $u_0 = [0, 0]^T$, $u_1 = [0, a]^T$, $u_2 = [a, 0]^T$, and $u_3 = [a, a]^T$ and $a$ is the frequency parameter. Thus, for a single image $f$, there are eight output response images, four of which are real response images $F_{re}^{u_m}$ and the other four are imaginary response images $F_{im}^{u_m}$. The LPQ code for each pixel $x$ is then encoded into a decimal number as

$$LPQ(x) = \sum_{i=0}^{3} \left( F_{re}^{u_m}(x) \geq 0 \right) \times 2^i + \left( F_{im}^{u_m}(x) \geq 0 \right) \times 2^{i+1}$$

(3)

where $l(\cdot) \in \{0, 1\}$ is an indication function of a boolean condition. By varying the frequency parameter $a$, multi-scale LPQ (MLPQ) features can be extracted.

3. Fast multi-scale LPQ extraction

The critical operator of MLQP extraction is the SFT in local region. Rewrite Eq. (2), we have

$$F(u, x) = \sum_{y \in N_k} f(x - y)e^{-j2\pi uy'} = \sum_{y \in N_k} f(x - y)e^{j2\pi uy'(x - y)} e^{-j2\pi uy'}$$

$$= e^{-j2\pi uy'} \sum_{y \in N_k} f(x - y)e^{j2\pi uy'(x - y)}$$

(4)

It is clear to see that $F(u, x)$ can be divided into two components. One is $e^{-j2\pi uy'}$ which is irrelevant with $y$, and the other is $\sum_{y \in N_k} f(x - y)e^{j2\pi uy'(x - y)}$ which is the summation of values of function $f(x)e^{j2\pi uy'}$ in certain region and can be computed efficiently with integral image.

The fast MLQP extraction algorithm is detailed as follows.

1. Given an image $f(x)$, the integral image $I(x)$ for $f(x)e^{j2\pi uy'}$ is computed as

$$l(x) = \sum_{y \in x} f(y)e^{j2\pi uy'}$$

(5)

2. Considering the rectangular area $R$ shown in Fig. 2. A. B. C. D are four vertices of the region and $E$ is the central point. The summation of $f(x)e^{j2\pi uy'}$ in this area can be computed as

$$\sum_{x \in R} f(x)e^{j2\pi uy'} = l(A) - l(B) - l(C) + l(D)$$

(6)

3. The SFT result for region $R$ is then obtained as

$$F(u, x) = e^{-j2\pi uy'} \{l(A) - l(B) - l(C) + l(D)\}$$

(7)

4. After we compute the SFT responses at different frequencies, the MLPQ code can be extracted following Eq. (3).

Suppose the image size is $h \times w$, and the scale of SFT is $M \times M$, it is easy to see that the complexity of the original SFT (Eq. (2)) for one image is $O(hwM^2)$, whereas the complexity of the proposed method is $O(hw)$ with a little more memory cost to store the integral images. The complexity of proposed method is irrelevant with the scale of SFT and hence is suitable and efficient for MLQP extraction. In our experiment, we find that the integral image based MLQP extraction method is about three times faster than the original convolution based one. In this work, $9$ scales are used to extract the over-complete MLPQ features. Fig. 3 shows an example of one image with its $9$ scale MLPQ results.

4. Feature selection and transformation

Refs. Ahonen et al. (2006, 2008) and Chan et al. (2009) partition the face image into non-overlapped regions uniformly to extract the MLQP histogram feature. However, the best sizes of histogram for different parts of face are different. It is not optimal to divide the face image with the same region size. Moreover, the non-overlapped partition may miss some important discriminant information at the intersection of two regions. To address these
problems, we adopt an alternative way to divide the face image into overlapped regions with various sizes. The feature dimension in this way increases dramatically and there exists large redundancy among features. In this paper, we utilize a data-driven method to select the most discriminative and representative features from the original feature pool to reduce the feature dimension and improve the precision of feature representation. Fig. 4 shows a comparison of uniform non-overlapped partition and feature selection based multi-scale overlapped partition methods.

4.1. Adaboost learning

Adaboost learning is an efficient method to ensemble a series of weak classifiers to obtain a strong classifier. Instead of learning a strong classifier directly, Adaboost can also be utilized as a feature selection tool if the weak classifiers are constructed based on different features. The weak classifiers (features) selected by Adaboost are thought to be of good complementary to each other and are effective to discriminate samples from different classes. Given a training set of $N$ labeled examples from two classes, $S = \{x_1, y_1\}, \ldots, \{x_N, y_N\}$, where $x_i$ is the data and $y_i \in \{+1, -1\}$ is the class label, the basic Adaboost learning procedure is shown in Fig. 5.

In this work, a weak classifier is defined based on a single feature (i.e. an MLPQ histogram bin value). A weak classifier gives an output of $+1$ or $-1$, by thresholding the feature at an appropriate threshold value learned with a weak learning procedure. In this way, a series of features (weak learners) can be selected using the Adaboost learning.

4.2. Regression based feature selection

The framework of integrating Adaboost (feature selection) and subspace learning (feature transformation) (Li et al., 2007) is one of the state-of-the-art methods in face recognition. Our work follows this direction. Though Adaboost learning is effective to select discriminative and complementary features for face recognition, its objective is not very consistent with subspace learning. In Adaboost learning, face recognition is treated as a two-class problem and the intra and inter face samples are created by computing the differences between samples from the same class and the different classes. Subspace learning treats the face recognition as a multi-class problem and aims to find the most discriminant subspace to separate the samples from different classes as far as possible and make the samples from the same class compact. Therefore, for subspace learning, Adaboost may not be the optimal choice for feature selection. Ref. Pang et al. (2004) uses linear discriminant analysis (LDA) to select the most discriminant pixels and Gabor features are extracted on these pixels to represent faces. However, traditional subspace learning methods involve eigenvalue decomposition, which is computational expensive, especially for high-dimension feature. In this paper, we propose a regression based feature selection method. Different from the work (Pang...
et al., 2004), which selects the key positions for Gabor feature extraction, our work tries to select the most discriminative features directly. It has at least two advantages over existing ones (Shan et al., 2005; Li et al., 2007; Pang et al., 2004). First, compared with Adaboost, its objective is more consistent with subspace learning. Second, by avoiding computational expensive eigenvalue decomposition operator, its solution can be obtained more efficiently than the method in Pang et al. (2004).

Least squares regression (LSR) is closely related to subspace learning. Taking LDA for example, in two-class case, the solution of LSR is proved to be equivalent to LDA if the prediction variable is properly defined (Duda et al., 2001). Here we use the LSR to determine the most discriminative features for C-class problem. Given the sample set \( X = [x_1, x_2, \ldots, x_N] \in \mathbb{R}^d \), where \( N \) is the total number of samples and \( d \) is the feature dimension, the prediction variable \( Y = [y_1, y_2, \ldots, y_N] \) is coded following the one-of-\( C \) rule. That is, if \( x_i \) belongs to the \( k \)th class, then \( y_i = [0, \ldots, 1, \ldots, 0] \in \mathbb{R}^C \), where the \( k \)th element is 1 and the others are 0. The LSR problem is formulated as to learn the mapping from the data to the output predictions.

**Fig. 3.** One face image (a) and its 9 scale MLPQ resultant images (b–j).

**Fig. 4.** Uniform non-overlapped partition vs. multi-scale overlapped partition.
The Adaboost learning procedure.

\[ W = \arg \min_W |Y - WX|^2 \]  \hspace{1cm} (8)

where \( W \) is a \( C \times d \) projective matrix. The solution for the above equation can be obtained as

\[ W = YX^T(XX^T)^{-1} \]  \hspace{1cm} (9)

or

\[ W = YX^T(XX^T + \lambda I)^{-1} \]  \hspace{1cm} (10)

in which \( \lambda \) is the trade-off parameter to improve the generalization of the solution. For large scale data, the solution can be computed efficiently by LSQR algorithm (Paige and Saunders, 1982). After that, we combine the row vectors of projective matrix \( W \) to determine the discriminant features as in Pang et al. (2004).

First, a new vector \( w \) is computed as

\[ w_j = \sum_{i=1}^C |W_{ij}| \]  \hspace{1cm} (11)

Second, the vector \( w \) is sorted in descending order to form the vector \( v \). The first \( m \) dimensions of vector \( v \) (corresponding to the \( m \) largest weights) are defined as the most important features for the subsequent subspace learning method.

In this paper, we combine the Adaboost and regression based method together to finish the feature selection task. Adaboost is first used to select a set of relatively abundant features from the huge original feature pool. The regression method is then applied to determine the most discriminative features proper for the subspace learning. The combination of these two methods improves the efficiency and accuracy of feature selection.

4.3. Subspace learning based feature transformation

Linear discriminant analysis (LDA) (Belhumeur et al., 1997) is a representative subspace learning method which has achieved great success in face recognition. In this part, we conduct LDA on the selected features to learn the most discriminant subspace for classification. The essential idea of LDA is to disperse the samples from different classes and meanwhile gather the samples from the same class. Given the training samples \( Z = (z_1, z_2, \ldots, z_k) \), the between class scatter matrix \( S_b \) and within class scatter matrix \( S_w \) are defined as

\[ S_b = \frac{1}{N} \sum_{i=1}^C |N_i(m_i - m)(m_i - m)^T | \]

\[ S_w = \frac{1}{N} \sum_{i=1}^C \sum_{j \neq i} (z_j - m_i)(z_j - m_i)^T \]  \hspace{1cm} (12)

where \( m_i = \frac{1}{N_i} \sum_{z \in C_i} z \), is the mean vector of data in class \( C_i \). \( L \) is the number of class and \( m = \frac{1}{N} \sum_{i=1}^C \sum_{j \in C_i} z_j \) is the global mean vector. LDA aims to find the projective direction \( W \) which maximizes the ratio of between class scatter matrix to within class scatter one as

\[ J = \frac{S_b}{S_w} = \frac{W^T S_b W}{W^T S_w W} \]  \hspace{1cm} (13)

The optimal projection matrix \( W_{opt} \) can be obtained by solving the following eigenvalue problem

\[ S_w W_{opt} = \Lambda W_{opt} \]  \hspace{1cm} (14)

where \( \Lambda \) is the diagonal matrix whose diagonal elements are eigenvalues of \( S_w^{-1} S_b \).

In classification phase, after projecting the original data onto discriminant subspace, cosine distance is utilized to measure the dissimilarity of two samples in subspace. In this work, only one subspace is learned for face recognition and hence it is computationally efficient.

5. Experiments

Two large face databases FERET (Phillips et al., 2000) and FRGC ver 2.0 (Phillips et al., 2005) are used to compare the proposed method with some state-of-the-art methods. In the first experiment, the MLQP feature is compared with MBLRP (Liao et al., 2007), which is one of the most successful face representations. Two feature selection methods (Adaboost vs. Adaboost-regression) are compared. These experiments are taken on FRGC ver 2.0 database following Exp. 1 and 4 protocols. In the second experiment, we test the classifier trained from FRGC on FERET database to examine the generalization performance of the proposed method.

5.1. Data description

The FERET 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, dup1 and dup2) including expression, illumination and aging variations. In this experiment, we don't use the training set and evaluate the performance of the classifier trained from FRGC directly on four probe sets and gallery set. All the images are rotated, scaled and cropped to 142 x 120 size according to the provided eye coordinates.

FRGC ver 2.0 was collected by the University of Notre Dame. The training set consists of 12,776 face images from 222 individuals, including 6360 controlled images and 6416 uncontrolled ones. In the test set, there are 16,028 controlled images from 466 persons including 6360 controlled images and 6416 uncontrolled ones. So the experiment 4 is much more difficult than experiment 1. All the images are rotated, scaled and cropped to 142 x 120 according to the provided eye positions.
5.2. Results and discussion

We first compare the computational cost of the original convolution based MLPQ extraction method with our integral image based one. The results are reported as the average CPU time of 20 runs on extracting 9 scale MLPQ features from one face image with unoptimized C++ code. In our implementation, the original MLPQ computation method takes 391 ms. In comparison, the proposed fast MLPQ extraction method only takes 109 ms, more than three times faster than the original one. It greatly improves the face recognition efficiency.

Now we compare the performance of different combinations of MLPQ, MBLBP with two feature selection methods. For MLPQ, 9 scales of SFT (i.e. \(M = 7, 9, 11, 13, 15, 17, 19, 21, 23\)) are used. For LPQ, the scale of SFT is set to 7. For the traditional Adaboost based feature selection method (denoted as FS\(^1\)), 2000 features are finally selected. For our two-step method (denoted as FS\(^2\)), Adaboost learning is firstly utilized to select 6000 feature candidates and regression is then applied to select 2000 features from 6000 ones. We also compare the two face image partition ways with MLPQ feature. For ease of representation, we use “MLPQ+” to denote the uniform non-overlapped partition way as in Ahonen et al. (2006) and in all other methods, the multi-scale overlapped partition way is adopted. In addition, we list the performance of BEE baseline (Phillips et al., 2005) and two state-of-the-methods (denoted as Hwang’s method (Hwang et al., 2006) and Liu’s method (Liu, 2006)) for comparison.

Table 1 shows the recognition results of different methods on FRGC ver 2.0 database. MLPQ related methods achieve better recognition performance than single LPQ, indicating that MLPQ explores more sufficient discriminant information for face recognition. Regarding the image partition method, MLPQ with multi-scale overlapped partition outperforms the MLPQ with uniform non-overlapped partition way, showing that the multi-scale overlapped partition way is the better one and is effective to improve face recognition performance. It is obvious that MLPQ achieves better performance than MBLBP. This indicates that MLPQ is not only robust to blur variation, but also effective for face recognition in general various conditions. Comparing the two feature selection methods using MBLBP or MLPQ feature, the proposed two-step feature selection method always outperforms the traditional Adaboost one, especially in more difficult experiment 4.

In order to examine the generalization ability of the proposed method, we use the model trained on FRGC training set to be tested on FERET database. The MLPQ+FS\(^2\) model which has the best performance on FRGC is used in this experiment. Table 2 shows the recognition results of the proposed method compared with some popular methods on FERET database following fb, fc, dup I and dup II protocols. It is worth noting this is a face recognition test across different databases. MLPQ+FS\(^2\) achieves comparable performance with state-of-the-art methods and it demonstrates the good generalization. Besides the accuracy, our proposed method is also more computational efficient than other methods. For example, the dimension of face representation for HGPP is (40 + 5) \(\times\) 64 \(\times\) 256 = 737,280 as configured in Zhang et al. (2007). In contrast, the feature dimension of proposed method is 221, which is less than 1/3000 length of HGPP. The computational cost of proposed method is much lower than HGPP in matching phase. In feature extraction process, HGPP deploys 40 Gabor complex convolution operators and 40 LBP operators on a face image, followed by histogram feature extraction based on all the Gabor images. For our method, it involves 36 (9 scales and 4 orientations) fast MLPQ operators and only the selected histogram features need to be computed from the MLPQ resultant images.

6. Conclusions

This paper proposes a fast MLPQ extraction algorithm with the help of integral images. Multi-scale LPQ and multi-scale histogram features are extracted from face images to consist a over-complete feature pool. A novel feature selection method combining Adaboost and regression is then utilized to select the most discriminative and suitable features for subspace learning. Following our method, only a small number of features need to be extracted from the face image in recognition phase, so it is efficient in terms of computational cost. Experiments on large benchmark databases demonstrate the good recognition and generalization performance of

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<th>Method</th>
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Table 2 Comparison results (recognition rates) of proposed method with state-of-the-art methods on FERET database. FS\(^2\) denotes the Adaboost+regression feature selection method.
the proposed method. Our future work is to combine the MLPQ with other local features like LBP, Gabor etc. to construct a practical face recognition system.

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