Yerel İkili Örüntü Ortamında Yerel Görünüme Dayalı Yüz Tanıma

Local Binary Pattern Domain Local Appearance Face Recognition

Hazım K. Ekenel[1], Mika Fischer[1], Erkin Tekeli[2], Rainer Stiefelhagen[1], Aytül Erçil[2]

[1]Institut für Theorestische Informatik, Universität Karlsruhe (TH), Karlsruhe, Germany
[2]Faculty of Engineering and Natural Sciences, Sabancı University, İstanbul, Turkey

{ekenel,mika.fischer,stiefel}@ira.uka.de, {erkintekeli,aytulercil}@sabanciuniv.edu

Özetçe

Bu bildiride, ayrık kosinüs dönüşümü tabanlı yerel görünüme dayalı yüz tanıma algoritması ile yüz imgelerinin yerel ikili örüntüye (YİÖ) dayalı betimlemesini birleştiren hızlı bir yüz tanıma algoritması sunulmuştur. Bu tümleştirmedeki amaç, yerel ikili örüntünün dayanıklı imge betimleme yeteneği ile ayrık kosinüs dönüşümünün derli-toplu veri betimleme yeteneğinden yararlanmaktır. Önerilen yaklaşımda, yerel görünümün modellenmesinden önce girdi yüz imgesi yerel ikili örüntü ile betimlenmiştir. Elde edilen YİÖ betimlemesi, birbirleri ile örtüşmeyen bloklara ayrılmış ve her blok üzerinde yerel özniteliklerin çıkartımı için ayrık kosinüs dönüşümü uygulanmıştır. Çıkartımı yapılan yerel öznitelikler daha sonra arka arkaya eklenerek global öznitelik vektörü oluşturulmuştur. Önerilen algoritma, CMU PIE ve FRGC versiyon 2 veritabanlarından seçilen yüz imgeleri üzerinde sınanmıştır. Deney sonuçları, tümleşik yöntemin başarımı önemli ölçüde arttırdığını göstermiştir.

Abstract

This paper presents a fast face recognition algorithm that combines the discrete cosine transform based local appearance face recognition technique with the local binary pattern (LBP) representation of the face images. The underlying idea is to benefit from both the robust image representation capability of local binary patterns, and the compact representation capability of local appearance-based face recognition. In the proposed method, prior to local appearance modeling, the input face image is transformed into the local binary pattern domain. The obtained LBP-representation is then decomposed into non-overlapping blocks and on each local block the discrete cosine transform is applied to extract the local features. The extracted local features are then concatenated to construct the overall feature vector. The proposed algorithm is tested extensively on the face images from the CMU PIE and the FRGC version 2 face databases. The experimental results show that the combined approach improves the performance significantly.

1. Introduction

Face recognition under uncontrolled conditions is a very difficult problem [1]. To solve this problem, the ongoing research on face recognition has focused on better representation of face images and efficient feature extraction from these image representations with the objective to obtain feature vectors that are less sensitive to the variations in the facial appearance.

Local binary pattern based face recognition has been recently proposed as a robust face recognition algorithm [2,3]. In this approach the image is represented by local binary patterns (LBP). In the LBP representation, instead of using raw intensity values of pixels, a pattern that reflects the relationships between the intensity values of the neighboring pixels is used. The local statistical distributions of the patterns are utilized as features to be used in classification. The approach has inspired many other algorithms on face recognition [4-10]. In [4], LBP is performed on Gabor filtered images and the obtained representation is used for face recognition the same way as in [2]. In [5], a new, "symmetry" based, discrimination concept is proposed to reduce the feature dimensionality. In [6,7], LBP is used for face verification. In [8-10], a boosting algorithm is used to obtain discriminative local binary patterns, and the found patterns are used for classification.

Local appearance-based face recognition using the discrete cosine transform has been proposed as a fast and generic approach [11,12] and does not require detection of any salient local regions, such as eyes, as in the modular or component based approaches [13,14]. The approach is extensively tested on the publicly available face databases and compared with the other well known face recognition approaches. The experimental results showed that the local appearance-based approach performs significantly better than the traditional face recognition approaches [11,12].

Although face recognition with local binary patterns has been proven to be a robust algorithm, it suffers from heavy computational load due to the very high dimensional feature vectors that are extracted by concatenating the LBP histograms obtained from each local region. On the other hand, local appearance-based face recognition using the discrete cosine transform (DCT) provides a fast solution. Nevertheless, it would be better to have a robust image representation as an input to the algorithm to further improve its performance. Considering these facts, in this paper, we propose a face recognition algorithm that benefits from both the local binary patterns' better image representation capability compared to directly using the intensity values of the pixels, and the discrete cosine transform's compact representation capability. The proposed algorithm is tested on the face images from the CMU PIE and FRGC version 2 face databases. The obtained results show that the combined approach performs significantly better than the individual algorithms.

2. Local Appearance Face Recognition Using DCT

DCT-based feature extraction for local appearance face recognition can be summarized as follows: A detected and normalized face image is divided into blocks of 8x8 pixels size. Then, the DCT is applied on each block. The obtained DCT coefficients are ordered using zig-zag scanning. From the ordered coefficients, M of them are selected according to a feature selection strategy, and then normalized resulting in an M-dimensional local feature vector. These extracted local features are then concatenated to represent the entire face image (Fig. 1). For details of the algorithm please see [11,12].

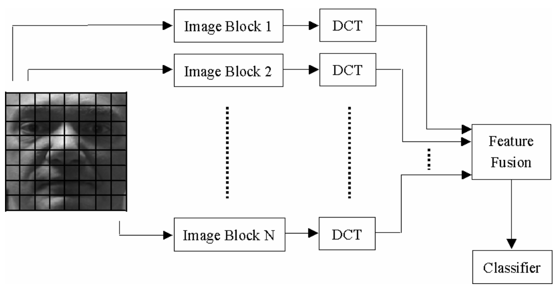

Figure 1. Feature extraction diagram for local appearance-based face recognition.

3. Face Recognition with LBP

The local binary pattern (LBP) operator is a non-parametric operator which is used for describing local spatial structure of an image. At a given pixel position, the LBP operator is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its neighbouring pixels. The LBP operator labels the pixels of the image by considering a neighborhood around each pixel and using the value of the center pixel to threshold the neighborhood. If the neighbouring pixel value is greater than or equal to the center pixel value this pixel takes 1 otherwise 0. Then an LBP code for a neighborhood is formed. The decimal value of this binary code represents the local structural information around the given pixel. The histogram of the LBP image shows how often these 256 different patterns occur in a given texture. The distribution of these patterns represents the whole structure of the texture. However, it is possible to decrease the number of patterns in an LBP histogram by only using uniform patterns without losing much information. An LBP pattern is a uniform pattern if it contains at most two bitwise transitions from 0 to 1 or 1 to 0 at its binary representation when the binary string is considered circular. For example, 11100001 (with 2 transitions) is a uniform pattern, whereas 11110101 (with 4 transitions) is a non-uniform pattern. There are totally 58 different uniform patterns at 8-bit LBP representation and when we assign the remaining patterns in one non-uniform binary number we can represent the texture structure with a 59-bin histogram instead of using 256 bins.

Face recognition with LBP is performed as follows. First, the input image is transformed to the LBP-domain. Afterwards, the obtained LBP image is divided into non-overlapping rectangular blocks. On each block, the histogram of local binary patterns is calculated. The obtained local histograms are then concatenated and used as feature vector for classification (Fig. 2).

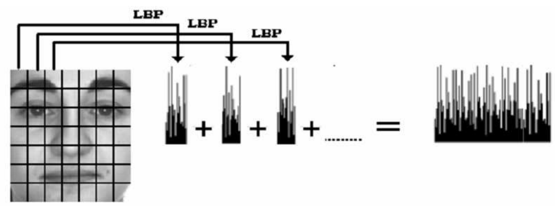

Figure 2. Feature extraction diagram for face recognition with local binary patterns.

4. LBP Domain Local Appearance Face Recognition

LBP domain local appearance face recognition combines the approaches presented in Sections 2 and 3. The rationale behind the fusion of these approaches is to utilize the individual benefits of both algorithms, while compensating their drawbacks at the same time. Local binary patterns have been shown to provide robust face representation in terms of having less sensitivity against variations that may occur on the facial appearance due to illumination, expression etc. [2,3]. In Fig. 3 within class variance to between class variance ratio of image representation techniques' is illustrated for each subject in order to show this property. These ratios are computed on the CMU PIE face database, which contains 68 subjects, by calculating first within class variance to between class variance ratio of each pixel's intensity value or local binary pattern value and then summing them up for each subject. As can be oberserved LBP representation provides lower ratio for most of the individuals. Nevertheless, LBP suffers from heavy computational load due to the resulting very high dimensional feature vectors that are obtained by concatenating the local LBP histograms. For instance, in the case of using only the uniform patterns, 59-dimensional features vectors are used to represent each local region. On the other hand, local appearance-based face recognition using the discrete cosine transform provides compact representation. It has been shown that using only five-dimensional feature vectors to represent the local regions suffices to achieve high performance [11,12]. However, it would be better to have a robust image representation as an input to the algorithm to further improve its performance. Taking these facts into consideration, we integrated the image representation part of LBP-based face recognition algorithm [2,3] with the feature extraction part of the local appearance-based face recognition algorithm [11,12]. Fig. 4 shows the resulting within class variance to between class variance ratio of DCT features for each subject. As can be seen, the DCT features extracted from LBP-images have lower ratio than the ones extracted from pixel intensity values.

The combined algorithm can be implemented as follows. The input image is first transformed to the LBP-domain. The obtained LBP-image is then divided into non-overlapping blocks of 8x8 pixels resolution. On each block the DCT is applied and the same feature extraction steps are performed as in the local appearance face recognition approach [11,12].

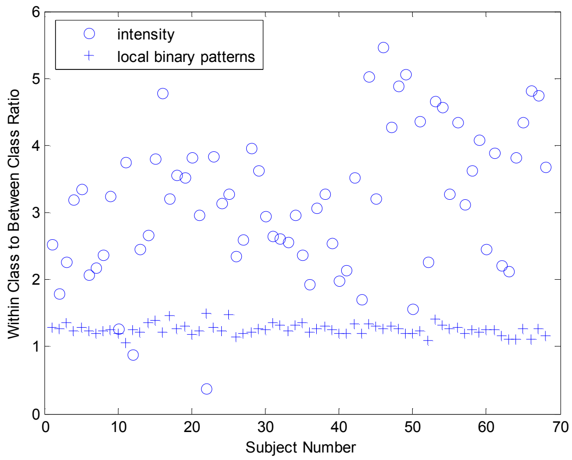

Figure 3. Within class variance to between class variance ratio of image representation for each subject in the CMU PIE face database.

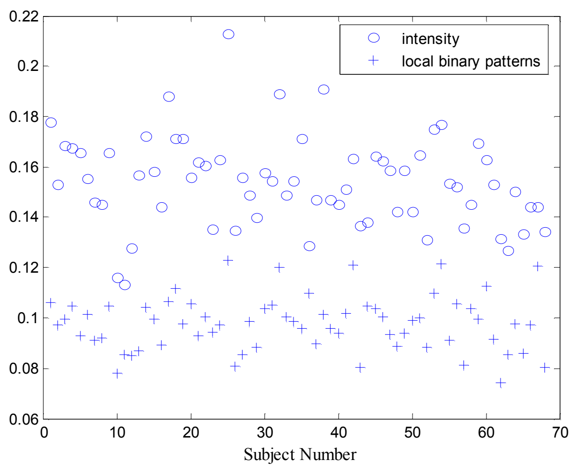

Figure 4. Within class variance to between class variance ratio of DCT features for each subject in the CMU PIE face database.

5. Experiments

The proposed local binary pattern domain local appearance face recognition algorithm is tested extensively on two different databases, the CMU PIE [15] and FRGC version 2 face databases [16]. In the CMU PIE face database, there are 68 subjects. 21 frontal face images of the subjects that belong to the illumination subset of the database are used in the experiments. The face image which is illuminated frontally, is used for training. The remaining twenty images that contain varying illumination are used for testing. Sample images from this database can be seen in Fig. 5. The data from the FRGC version 2 face database consists of 2400 face images of 120 individuals that are collected under uncontrolled conditions. Each individual in the face database has 20 face images. Ten of these images that were recorded during fall 2003, are used for training, whereas the remaining ten, that were recorded during spring 2004, are used for testing. Sample images from this database are shown in Fig. 6. All the face images are cropped and aligned using the eye center locations.

Figure 5. Sample images from the CMU PIE face database. The first image from the left is a sample training image. The others are sample testing images.

Figure 6. Sample images from the FRGC version 2 data set. The first two images from the left are sample training images. The others are sample testing images.

For classification, the nearest neighbour classifier is used. Two different metrics are evaluated comparatively, namely, the L1 distance, which is shown to perform better than Euclidean distance and normalized correlation [12], and the Chi square statistic, which is shown to perform better than histogram intersection and log-likelihood statistic [2], defined as follows:

L1 distance:

$$d = \sum_{m=1}^{M} \left| f_{training,m} - f_{test,m} \right|$$

Chi square statistic:

$$\chi^2 = \sum_{m=1}^{M} \frac{(f_{training,m} - f_{test,m})^2}{f_{training,m} + f_{test,m}}$$

where $f_{\mathrm{training,m}}$ is the m^{th} ($m = 1,\ldots,M$) component of the M-dimensional training feature vector, and similarly for $f_{\mathrm{test,\ m}}$. Unlike histogram values, since the features that are extracted from DCT coefficients can also have negative values, absolute values of these features are used while calculating the Chi-square statistic.

For comparison purposes, in addition to local binary pattern domain local appearance face recognition, the individual algorithms -face recognition with LBP [2,3], and local appearance face recognition [11,12]- are also tested separately on the same data sets.

Table 1 and 2 show correct recognition results obtained by the LBP-based face recognition algorithm, the local appearance face recognition algorithm (LAFR) and the LBP-domain local appearance face recognition algorithm on the CMU PIE and FRGC version 2 face databases. First, the algorithm is tested using the $\mathrm{LBP}_{8,2}^{\mathrm{u2}}$ operator -uniform patterns in a circular (8,2) neighborhood, that is, having 8 sampling points on a circle of radius of 2 pixels-, on face images of 150x130 pixels resolution that are divided into non-overlapping blocks of 21x18 pixels resolution as in [3]. The results obtained with this parameter setup are given in the first rows of Tables 1 and 2. The algorithm is also tested using the same operator on the same data sets, but this time the face images are resized to 64x64 pixels resolution and divided into 8x8 pixels resolution non-overlapping blocks, which is the parameter setup in local appearance face recognition [11,12]. The corresponding results are given in the second rows of Tables 1 and 2. As can be seen, the correct recognition rate is significantly better when using 64x64 pixels resolution face images that are divided into 8x8 pixels blocks. No significant performance difference between the L1 distance and the Chi square statistic is observed.

Table 1. Correct classification results of the LBP-based face recognition algorithm, the local appearance face recognition algorithm (LAFR) and the LBP-domain local appearance face recognition algorithm on the CMU PIE face database.

	L1	**Chi Square**
$LBP^{u2}_{8,2}$, 150x130	85.9%	85.7%
$LBP^{u2}_{8,2}$, 64x64	88.3%	88.9%
LAFR, 64x64	96.9%	96.7%
LBP domain LAFR, 64x64	**99.0%**	**99.0%**

Table 2. Correct classification results of the LBP-based face recognition algorithm, the local appearance face recognition algorithm (LAFR) and the LBP-domain local appearance face recognition algorithm on the FRGC ver. 2 face database.

	L1	**Chi Square**
$LBP^{u2}_{8,2}$, 150x130	75.5%	74.6%
$LBP^{u2}_{8,2}$, 64x64	81.8%	81.5%
LAFR, 64x64	80.6%	79.5%
LBP domain LAFR, 64x64	**84.0%**	**84.4%**

The correct recognition rates of the local appearance face recognition (LAFR) algorithm and the local binary pattern domain local appearance face recognition algorithms are shown in the third and fourth rows of Tables 1 and 2. Five-dimensional local feature vectors are used in local appearance face recognition and LBP-domain LAFR algorithms resulting 320-dimensional feature vectors in order to represent the entire image. Recall that 59-dimensional local feature vectors resulting 3776-dimensional feature vectors are used in the LBP-based face recognition algorithm. Compared to the results in the second rows of Tables 1 and 2, the LAFR algorithm is found to be superior to the face recognition with LBP algorithm under illumination variations. Under the uncontrolled conditions, as in the case with the face images from the FRGC version 2 database, face recognition with LBP performs slightly better. As can be observed, the combined approach improves the correct recognition rates on both of the databases. Again, no significant performance difference between the L1 distance and the Chi square statistic is observed.

6. Conclusion

In this paper, we present a fast and robust face recognition algorithm that combines the LBP-based [2,3] and local appearance-based [11,12] face recognition algorithms. The combined approach benefits from both the robust image representation capability of local binary patterns and the low dimensional feature representation capability of discrete cosine transform coefficients. This provides significant improvement in the correct recognition rate compared to each individual algorithm, while keeping the algorithm fast and efficient. The local feature vector used in the combined approach is five-dimensional, which is much lower than the 59-dimensional one used in face recognition with LBP [3].

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8. References

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