Face Description with Local Binary Patterns: Application to Face Recognition

Speak by

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Method

Facial image representation based on Local binary patter (LBP) texture features.

Face image-> several region-> extract and concatenate LBP feature distributions into an vector which used as a face descriptor.

Assessed the performance of the method in Face recognition problem under different situation and other applications, extensions are discussed as well.

Introduction

Face analysis includes:

1. Face detection

2. Face recognition

3. Facial expression recognition

Main Issue of Face Analysis: Finding efficient descriptors for face appearance.

Different holistic methods:
1: Principal Component Analysis (PCA)
2: Linear Discriminant Analysis (LDA)
3: 2-D PCA

Finally, local descriptors gained attention due to their robustness to challenges such as pose and illumination changes

Eigenfeatures Method:

1: One of the first face descriptors based on information extracted from local regions.

2: hybrid approach in which the features are obtained by performing Principal Component Analysis (PCA) to local face regions independently.

Local Feature Analysis:

1: extract information about local facial components
->kernels of local spatial support are used

2: Elastic Bunch Graph Matching (EBGM): describes faces using Gabor filter responses in certain facial landmarks and a graph describing the spatial relations of these landmarks.

Elastic Bunch Graph Matching (EBGM)

Use a small set of sample image graphs construct bunch graph and the image graph extraction is based on this approach. And recognition is based on a straightforward comparison of image graphs.

Local Photometric Feature Method: detect interest points or regions in images, perform normalization with respect to affine transformations and describe the normalized interest regions using local descriptors.

Conclusion: Not suited for face description. -> does not retain information on the spatial setting of the detected local region.

LBP Based Face Description:

1: one of the best performing texture descriptors and widely used in various applications.

2: It has proven to be highly discriminative and because its invariance to monotonic gray level changes and computational efficiency, make it suitable for demanding image analysis tasks.

Why LBP for Face Description?

Face can be seen as a composition of micro-patterns which can be well described by LBP operator.

Basic LBP operator

The histogram of the labels used as a texture descriptor.

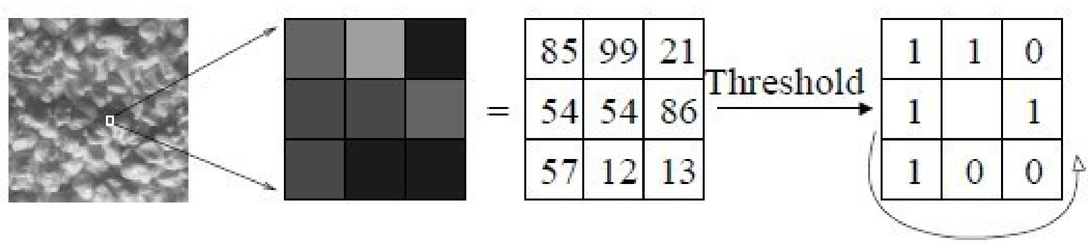

Fig. 1. The basic LBP operator.

The LBP operator was originally designed for texture description. The operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering the result as a binary number.

Texture at different scale?

1. Extend LBP operator to use neighborhoods of different sizes.
2. Defining the local neighborhood as a set of sampling points evenly spaced on a circle centered at the pixel to be labeled allows any radius and number of sampling points. 3. If a sampling point does not fall in the center of a pixel using Bilinear interpolation.

Let’s see Figure 2

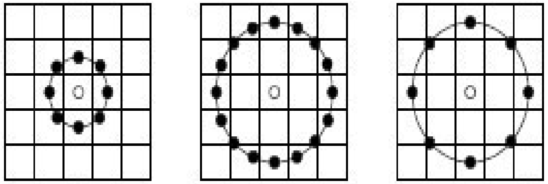

Fig. 2. The circular (8,1), (16,2) and (8,2) neighborhoods. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel.

Texture at different scale?

1. Extend LBP operator to use neighborhoods of different sizes.

Uniform Pattern: A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular

EX.

The patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform.

The patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not uniform.

In the computation of the LBP histogram, uniform patterns are used so that the histogram has a separate bin for every uniform pattern and all non-uniform patterns are assigned to a single bin.

Ojala *et al.* noticed that in their experiments with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8,1) neighborhood and for around 70 % in the
(16,2) neighborhood. We have found that 90.6 % of the patterns in the (8,1) neighborhood and 85.2 % of the patterns in the (8,2) neighborhood are uniform in case of preprocessed FERET facial images.

Notation for LBP Operator

$$\mathrm{LBP}_{P,R}^{u2}$$

U2 stands for using only uniform patterns.

The subscript represents using the operator in a (P, R) neighborhood.

Face description with LBP

They using the texture descriptor to build several local descriptions of the face and combining them into a global description.

Why not selecting the local feature based approach instead of finding a holistic description?

1: The local feature based or hybrid approaches to face recognition have been gaining interest lately which is understandable given the limitations of the holistic representations and these methods are more robust against variations in pose or illumination than holistic methods.

Why not selecting the local feature based approach instead of finding a holistic description?

2: Trying to build a holistic description of a face using texture methods is not reasonable.

For face, retaining the information about spatial relations is important. But texture descriptors tend to average over the image area. It suppose the face is like ordinary textures, texture description should usually be invariant to translation or even rotation of the texture. The small repetitive textures, the small-scale relationships determine the appearance of the texture and thus the large-scale relations do not contain useful information. However, for face, not.

Face Description with Local Binary Patterns

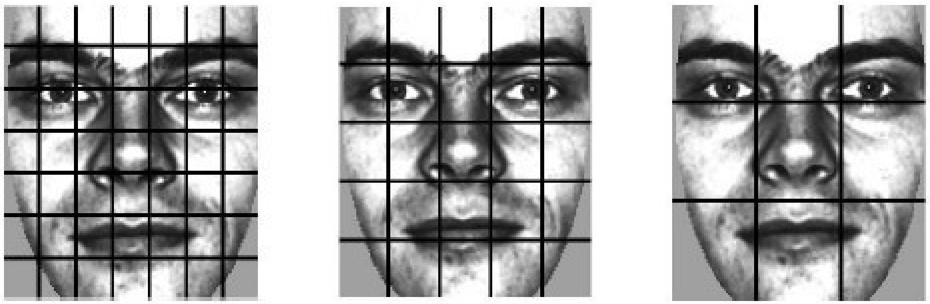

Fig. 3. A facial image divided into 7×7, 5×5 and 3×3 rectangular regions.

The facial image is divided into local regions and texture descriptors are extracted from each region independently.

The descriptors are then concatenated to form a global description of the face.

Description of the face on three different levels of locality

1: The LBP labels for the histogram contain information about the patterns on a pixel-level
2: The labels are summed over a small region to produce information on a regional level
3: The regional histograms are concatenated to build a global description of the face.

Improve spatially enhanced histogram by defining the distance measure

1: Psychophysical findings indicate that some facial features (such as eyes) play more important roles in human face recognition than other features
2: Assume the regions can be weighted based on the importance of the information they contain.

$$\chi_w^2(\mathbf{x}, \boldsymbol{\xi}) = \sum_{j,i} w_j \frac{(x_{i,j} - \xi_{i,j})^2}{x_{i,j} + \xi_{i,j}}, \tag{1}$$

in which x and ξ are the normalized enhanced histograms to be compared, indices i and j refer to i-th bin in histogram corresponding to the j-th local region and w_j is the weight for region j.

Experimental Analysis

Our approach is assessed on the face recognition problem using the Colorado State University Face Identification Evaluation System with images from the FERET database. PCA , Bayesian Intra/Extrapersonal Classifier (BIC) and EBGM were used as control algorithms.

Experimental Setup

1: Using CSU face identification evaluation system to test the performance of the proposed algorithm.
2: Using the FERET face images and follows the procedure of the FERET test for semiautomatic
face recognition algorithms [18] with slight modifications.
3: The images contain variations in lighting, facial expressions, pose angle etc. In this work, only frontal faces are considered.

Dividing facial images into five sets

fa set, used as a gallery set, contains frontal images of 1196 people.

fb set (1195 images). The subjects were asked for an alternative facial expression than in the *fa* photograph.

fc set (194 images). The photos were taken under different lighting conditions.

dup I set (722 images). The photos were taken later in time.

dup II set (234 images). This is a subset of the *dup I* set containing those images that were taken at least a year after the corresponding gallery image.

Along with recognition rates at rank 1, two statistical measures are used to compare the performance of the algorithms:

1: The mean recognition rate with a 95 % confidence interval and the probability of one algorithm outperforming another.

2: The probability of one algorithm outperforming another is denoted by P(R(alg1) >R(alg2)). These statistics are computed by permuting the gallery and probe sets.

Parameters of the LBP method

There are some parameters that can be chosen to optimize the performance of the LBP-based algorithm.

1: choosing the type of the LBP operator
2: division of the images intoregions R0,…,Rm-1
3: selecting the distance measure for the nearest neighbor classifier
4: finding the weights wj for the weighted X^2 statistic (Equation 1).

Face Description with Local Binary Patterns

(a) (b)

Fig. 4. (a) A facial image divided into 7x7 windows. (b) The weights set for the weighted χ^2 dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0 and white 4.0.

The obtained weights are illustrated in Figure 4 (b). The weights were selected without utilizing an actual optimization procedure and thus they are probably not optimal. Despite that, in comparison with the non-weighted method, an improvement both in the processing time and recognition rate (P(R(weighted) =R(non-weighted))=0.976) was obtained.

Comparing LBP to other local descriptors

Why the tested methods work well with the easiest fb probe set?

They are robust with respect to variations of facial expressions, whereas the results with the *fc* probe set show that other methods than LBP do not survive changes in illumination.

TABLE I

THE RECOGNITION RATES OBTAINED USING DIFFERENT TEXTURE DESCRIPTORS FOR LOCAL FACIAL REGIONS. THE FIRST FOUR COLUMNS SHOW THE RECOGNITION RATES FOR THE FERET TEST SETS AND THE LAST THREE COLUMNS CONTAIN THE MEAN RECOGNITION RATE OF THE PERMUTATION TEST WITH A 95 % CONFIDENCE INTERVAL.

Method	**fb**	**fc**	**dup I**	**dup II**	**lower**	**mean**	**upper**
Difference histogram	0.87	0.12	0.39	0.25	0.58	0.63	0.68
Homogeneous texture	0.86	0.04	0.37	0.21	0.58	0.62	0.68
Texton Histogram	0.97	0.28	0.59	0.42	0.71	0.76	0.80
LBP (nonweighted)	0.93	0.51	0.61	0.50	0.71	0.76	0.81

Comparing LBP to other local descriptors

Why LBP has better performance?

1: Its tolerance to monotonic gray-scale changes.
2: The computational efficiency of the LBP operator and that no gray-scale normalization is needed prior to applying the LBP operator to the face image.

Rank curves

LBP has higher recognition rates than the control algorithms in all the FERET test sets and in the statistical test

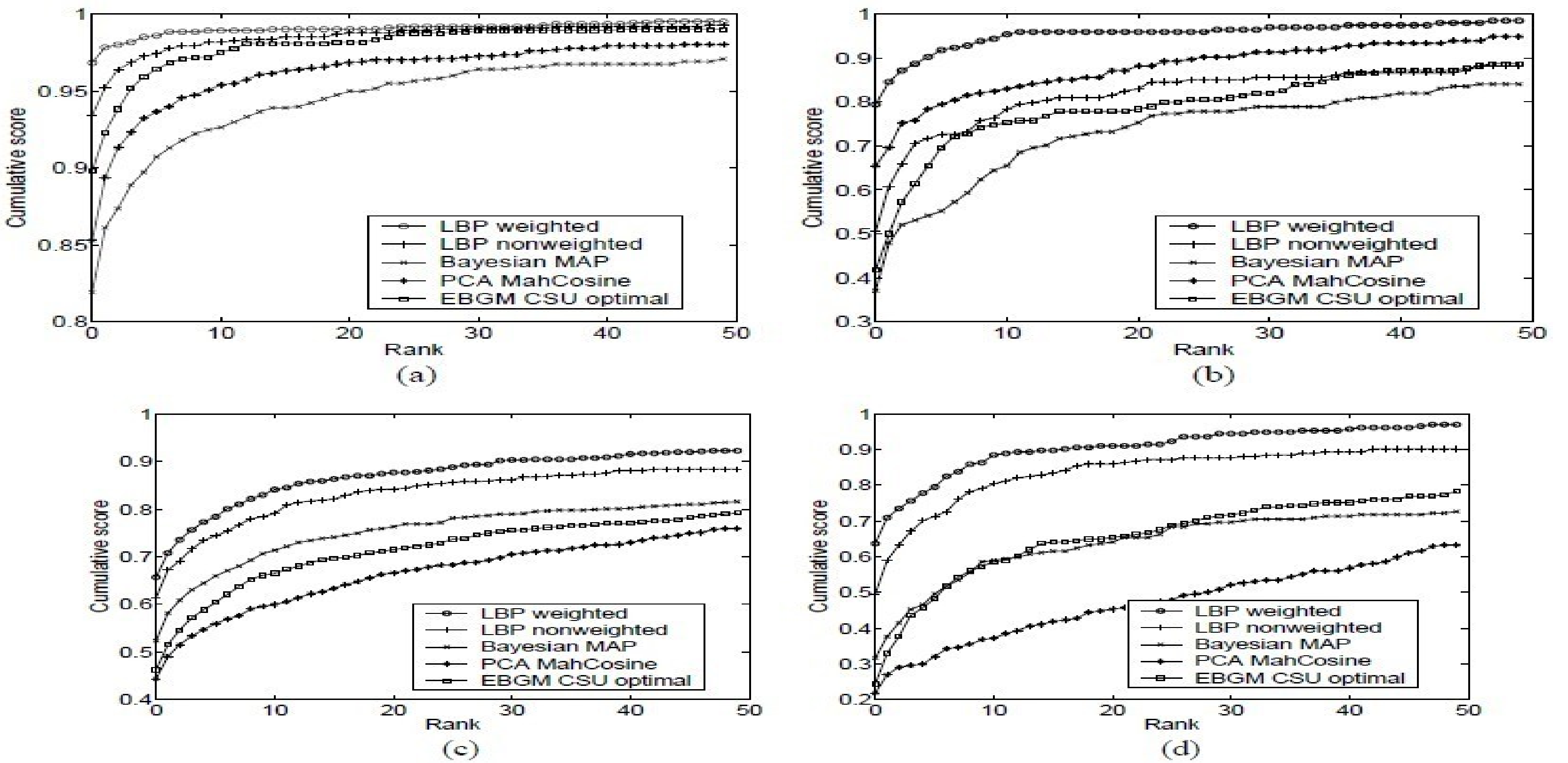

Fig. 5. The cumulative scores of the LBP and control algorithms on the (a) *fb*, (b) *fc*, (c) *dup I* and (d) *dup II* probe sets.

Final Recognition Results

TABLE II

THE RECOGNITION RATES OF THE LBP AND COMPARISON ALGORITHMS.

Method	fb	fc	dup I	dup II	lower	mean	upper
LBP, weighted	0.97	0.79	0.66	0.64	0.76	0.81	0.85
LBP, nonweighted	0.93	0.51	0.61	0.50	0.71	0.76	0.81
PCA, MahCosine	0.85	0.65	0.44	0.22	0.66	0.72	0.78
Bayesian, MAP	0.82	0.37	0.52	0.32	0.67	0.72	0.78
EBGM_Optimal	0.90	0.42	0.46	0.24	0.61	0.66	0.71

Final Recognition Results

The results on the *fc* and *dup II* sets show that especially with weighting, the LBP based description is robust to challenges caused by lighting changes or aging of the subjects but further research is still needed to achieve even better performance.

Robustness of the method to face localization error

Real-world face recognition systems need to perform face detection prior to face recognition. Automatic face localization may not be completely accurate so it is desirable that face recognition works under small localization errors.

The effect of localization errors to recognition rate of the proposed method compared to PCA MahCosine

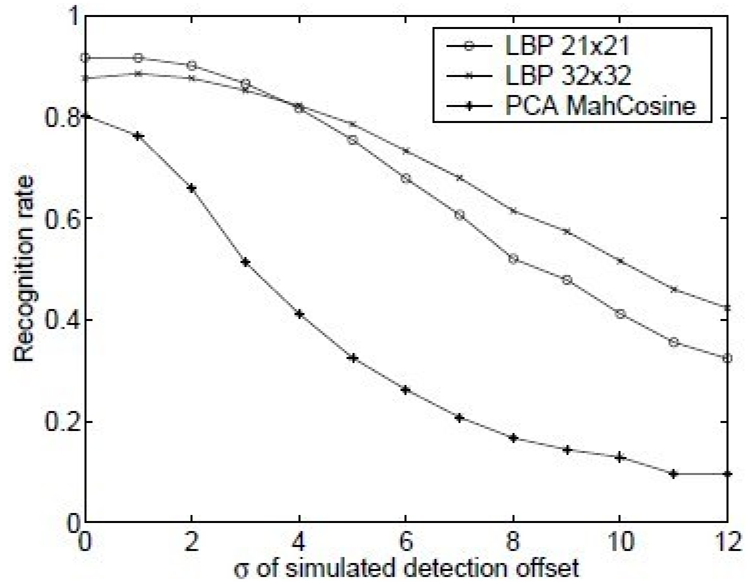

Fig. 6. The recognition rate for the *fb* set of two LBP based methods and PCA MahCosine as a function the standard deviation of a simulated localization error.

Conclusion of the test

It can be seen that when no error or only a small error is present, LBP with small local regions works well but as the localization error increases, using larger local regions produces better recognition rate. Most interestingly, the recognition rate of the local region based methods drops significantly slower than that of PCA.

Future work:

1. Studying more advanced methods for dividing the facial image into local regions and finding the weights for them.

2: Looking for image preprocessing methods and descriptors that are more robust against image transformations that change the appearance of the surface texture.

3: LBP features for facial expression recognition has been studied.

Pros:

1. A novel and efficient facial representation is proposed precisely.
2. LBP based face description has already attained an established position in face analysis research and many research group already study about it.
3. The recognition rates of the LBP perform pretty good than other comparison algorithm presented in this paper.
4. The recognition rates of the LBP maintain high level under the effect of localization errors.

Face Description with Local Binary Patterns

Cons:

1. Lack of detail about the research in the past, many are reference so that we can’t follow well to the method.
2. Further research is still needed to achieve even

better performance in the recognition rates of LBP.

3. Didn’t give the method whether we can improve the recognition rates of the LBP under the effect of localization errors.

Just for fun: Instead of clear mathematic induction, there are too much English description result in time consuming reading!