Face Description with Local Binary Patterns: Application to Face Recognition

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Overview

- Introduction
- Why LBP Based Face Description
- Local Binary Patterns
- Face Description with LBP
- Results
- Conclusion

Introduction

- Holistic approach such as PCA, LDA and 2-D PCA has been studied
- Something more Robust to challenges (ex. pose and illumination)
- Local descriptors are proposed to extract texture features from local facial regions
- LBP features outperformed global approaches

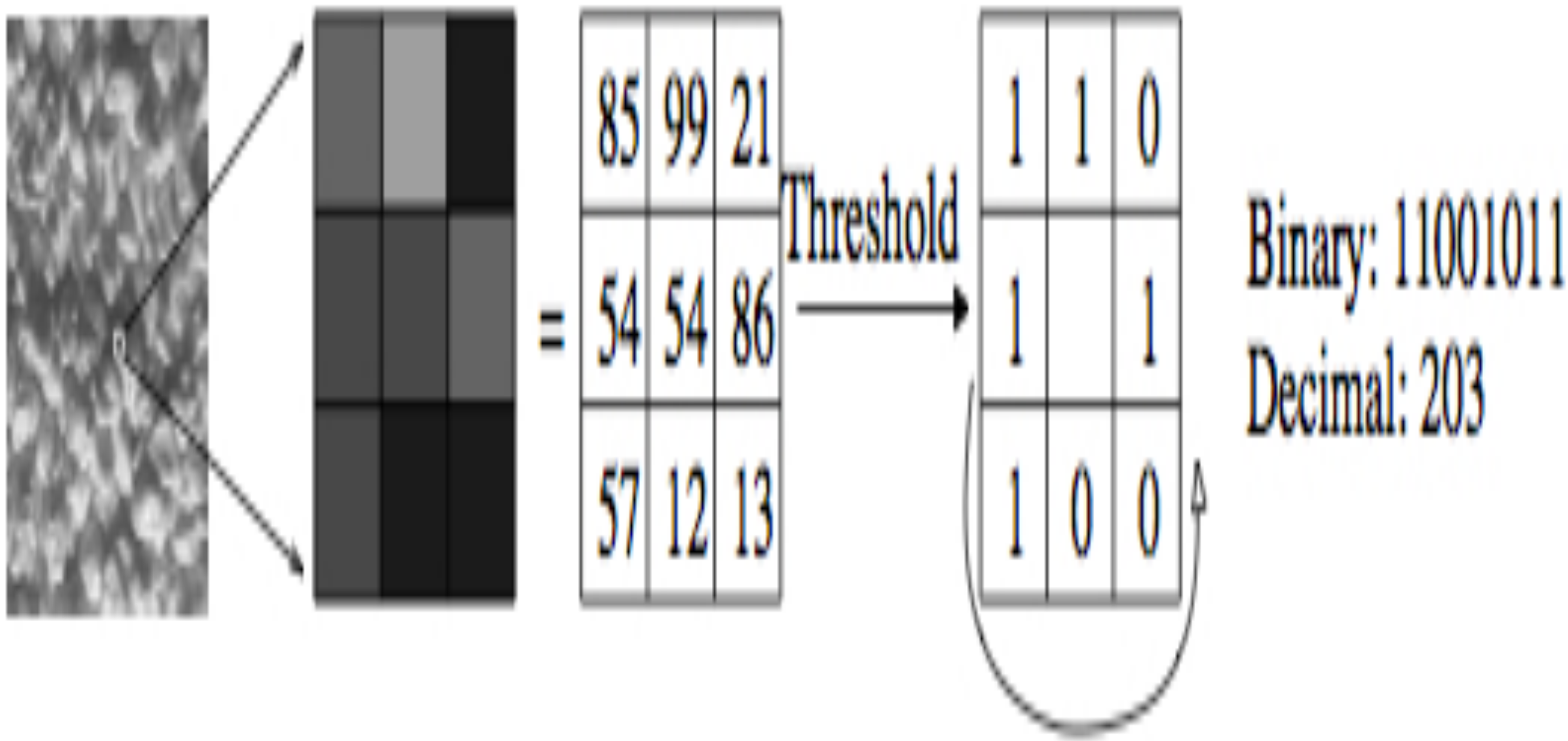
Why LBP Based Face Description

- Highly discriminative
- Invariant to monotonic gray level changes
- Computationally efficient

Local Binary Patterns

1. Operator assigns a label to every pixel
2. Use center pixel value to threshold the 3x3 neighborhood
3. Result in binary number
4. Preform Histogram on labels to use as texture descriptor

Local Binary Patterns

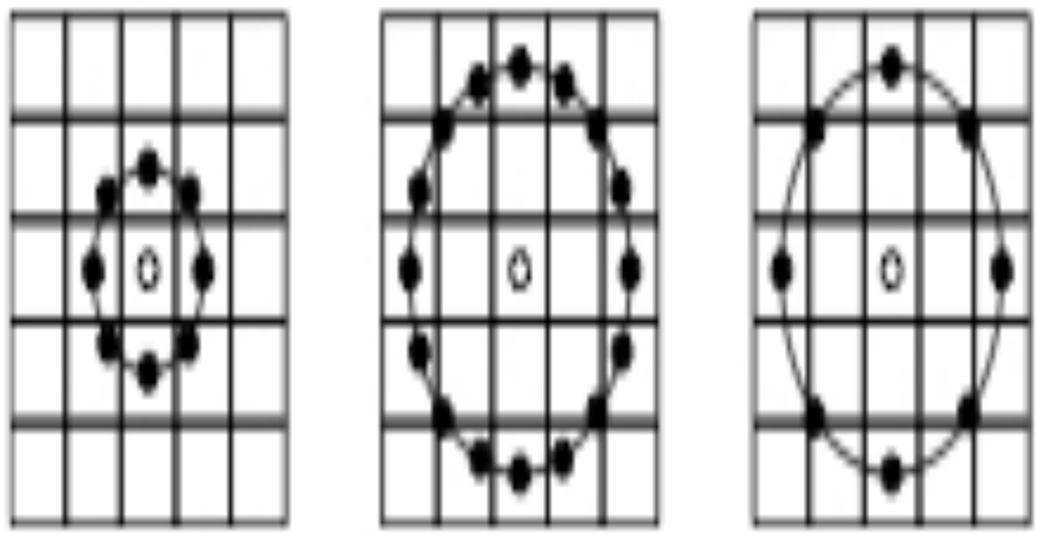


Local Binary Patterns

- LBP is extended to use different neighborhood sizes
- Local neighborhoods is defined as a set of sampling points evenly spaced on a circle centered at the labeled pixel.
- Bilinear interpolation is used if sampling point is not in the center of the pixel

Local Binary Patterns

- (P,R)
- (8,1)
- (16,2)
- (8,2)



Local Binary Patterns

- Uniform patterns to further improve LBP
- Histogram assigns separate bin for every uniform pattern
- Histogram assigns a single bin for all non-uniform pattern

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

Local Binary Patterns

- Uniform patterns is added (at most 2 transitions)
- Uniform patterns examples:
  - 00000000 (0 transitions)
  - 01110000 (2 transitions)
  - 11001111 (2 transitions)
- Non-uniform patterns examples :
  - 11001001 (4 transitions)
  - 01010011 (6 transitions)

Face Description with LBP

1. Facial image divided into local regions
2. Texture descriptors are extracted from each region
3. Descriptors are linked to form a global description of the face

Face Description with LBP

- **Spatially enhanced histogram** to encode appearance and spatial relations of facial regions
- m facial regions: R_0, R_1 ,…R_{m-1}
- Histogram computed independently
- Independent histogram are combined to form Spatially enhanced histogram (m x n)
- n = single LBP histogram length

Face Description with LBP

- Specific facial features contain more important information
- **Chi square distance** is utilized
- x and ξ= normalized enhanced histograms
- i= histogram index
- j= local region index
- wj= weight of region j

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

Face Description with LBP

8

(a) (b)

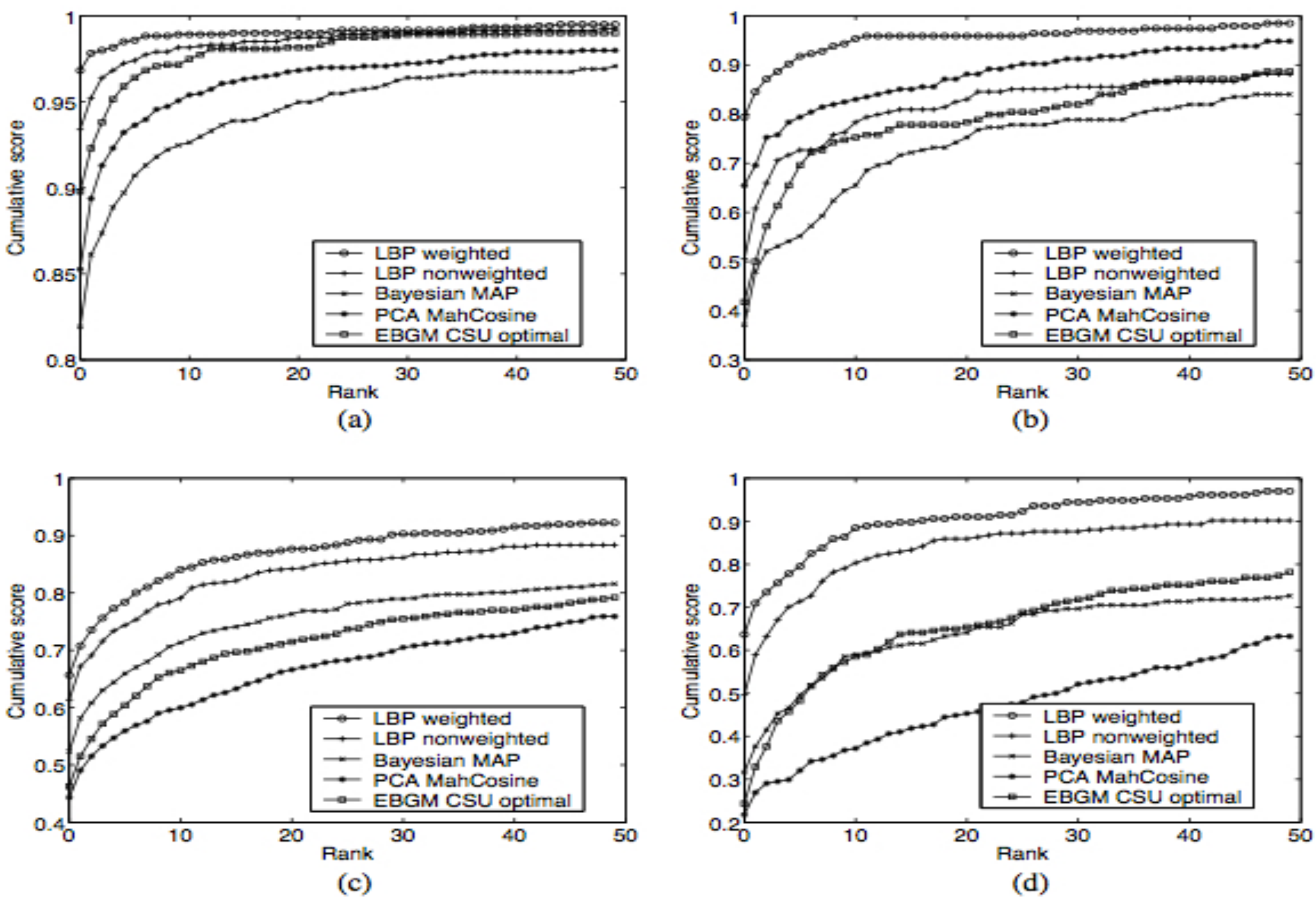
Fig. 4. (a) A facial image divided into 7x7 windows. (b) The weights set for the weighted χ^2 dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0 and white

Results

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

- Recognition rate

Results



Cumulative score
Rank
LBP weighted
LBP nonweighted
Bayesian MAP
PCA MahCosine
EBGM CSU optimal
0
10
20
30
40
50
0.8
0.85
0.9
0.95
1
(a)
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
(b)
0.4
0.5
0.6
0.7
0.8
0.9
1
(c)
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
(d)

Results

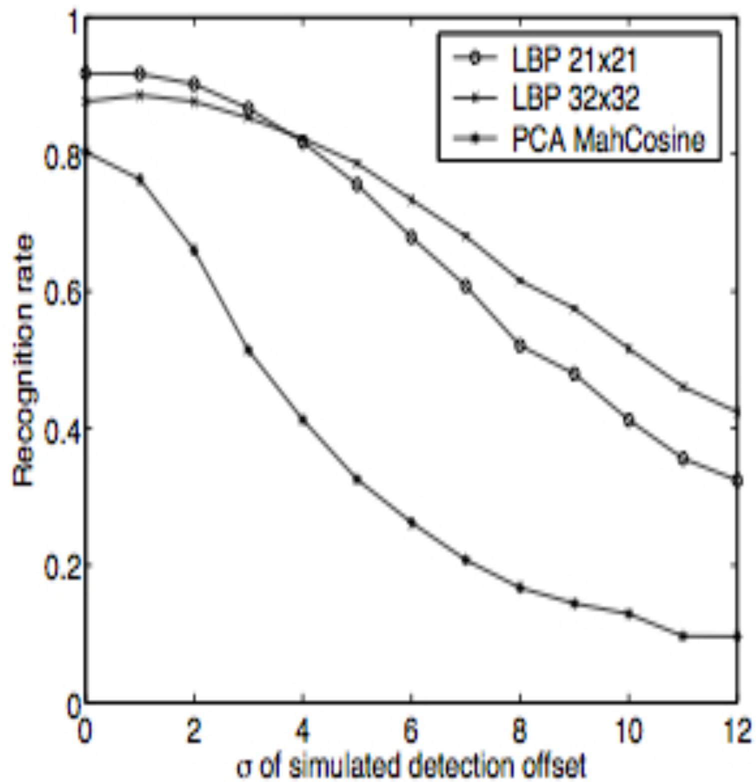


Fig. 6. The recognition rate for the *fb* set of two LBP based methods and PCA MahCosine as a function the standard deviation of a simulated localization error.

Conclusion

- Proposed method is based on dividing a facial images into small region
- Compute description of each region using LBP
- Descriptors are combined into a enhanced histogram
- Combining each region texture description forms global geometry of the face
- LBP outperformed all other methods