Face Description with Local Binary Patterns: Application to Face Recognition

Timo Ahonen (University of Oulu) et al.
IEEE TPAMI 2006

Presented by Wang Lin
2019. 09. 27

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Abstract

• This LBP method is an efficient facial image representation based on LBP texture features.

• Divide the face image into several regions, extract LBP feature distributions from these regions and concatenated into an enhanced feature histogram to be used as a face descriptor.
Introduction
Face Recognition Process

• Key issue in face analysis → finding efficient descriptor for face appearance.
Previous Work

• **Holistic methods** → PCA, LDA, describe full face attributes, such as skin color, outline, and facial organ distribution. It is only used for rough matching.

• **Local region methods** → EBGM, LBP, mainly describes the details of the face, such as the characteristics of the facial organs and some features of the face (black sputum, scars, dimples, etc.) for accurate confirmation.
Holistic Methods

PCA: Principal Component Analysis (1/2)

- Reduce dimensions of high dimensional data
  - “A hyperplane”
    - The distance from the sample points to this hyperplane is close enough.
    - The projection of the sample points on this hyperplane can be separated as much as possible.
“Eigenfaces for Recognition”
Holistic Methods

LDA : Linear Discriminant Analysis (1/2)

- Reduce dimensions of high dimensional data
- Choose the best projection direction for classification performance

![Graphs showing data points and projections](image)
Holistic Methods

LDA : Linear Discriminant Analysis (2/2)

“Discriminant Analysis for Recognition of Human Face Images”
[K. Etemad(University of Maryland) et al. /J. Optical Soc. Am., 1997]
Local Region Methods

EBGM: Elastic Bunch Graph Matching

• Express a face as consisting of several main feature points and join the feature points into a grid
  ▪ Node: a set of two-dimensional Gabor wavelet transform coefficients that describe the local features of the face.
  ▪ Edge: metric information describing the adjacent two nodes to the corresponding position.
• Identification based on the similarity of Gabor filter responses at each Gabor node.

“Face Recognition by Elastic Bunch Graph Matching”
[L. Wiskott(University of Southern California) et al. /IEEE TPAMI, 1997]
Local Region Methods

Advantage and Goal

- Advantage of the local analysis methods
  - Robust for illumination changes and pose changes.

- The goal of local methods
  - Finding good descriptors for the appearance of local facial regions.
    - Easy to compute.
    - Robust with the aging of the subjects, alternating illumination and other factors.

- In this paper, a descriptor based on local binary pattern texture features is proposed.
Local Region Methods

LBP : Local Binary Patterns

• “Face Recognition with Local Binary Patterns”
  - [T. Ahonen(University of Oulu) et al. /ECCV 2004]

![Diagram of LBP](image)

- Kinds of LBP
  - Original Local Binary Patterns
  - Circular Local Binary Patterns
  - Uniform Local Binary Patterns
LBP-Based Face Description
Original Local Binary Patterns

- Original LBP operator
  - One the best performing texture descriptors.
  - A label is assigned to every pixel.
  - Use center pixel value to threshold the 3x3 neighborhood.
  - Result in binary number.
  - Histogram of the labels is used as a texture descriptor.

Fig. 1. The basic LBP operator.
Circular Local Binary Patterns (1/2)

- Neighborhoods of Circular LBP
  - LBP is extended to use different sizes of neighborhoods.
  - Local neighborhoods is defined as a set of **sampling points**.
  - Points evenly spaced on a circle centered at the labeled pixel.
  - \((P,R)\) \(P = \text{the number of sampling points , } R = \text{radius}\)

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.
Circular Local Binary Patterns (2/2)

- Rotation invariance
  - the circular neighborhood is rotated to obtain a series of LBP values, and the minimum value is taken as the LBP value of the neighborhood.
Uniform Local Binary Patterns

• Features of Uniform pattern LBP
  ▪ Uniform pattern to further improve LBP.
  ▪ Uniform pattern has at most 2 bitwise transitions in binary pattern (0->1 or 1->0).
  ▪ Non-Uniform pattern is a bit sequence with more than 2 bitwise transitions (0->1 or 1->0).
  ▪ Binary patterns is greatly reduced: $2^P - P(P-1) + 2 + 1$
  ▪ Histogram assigns separate bin for every uniform pattern.
  ▪ Histogram assigns a single bin for all non-uniform pattern.
Uniform LBP Examples

- Example in case of (8, R)
  - Uniform patterns examples
    - 00000000 (0 transition)
    - 01111111 (1 transition)
    - 11001111 (2 transitions)
  - Non-uniform patterns examples
    - 11001001 (4 transitions)
    - 01010011 (5 transitions)
  - 59 bins histogram
    - Length of feature vector
      - 58 uniform patterns
      - 1 non-uniform pattern

The 58 different uniform patterns in (8, R) neighborhood
Uniform Patterns Examples

256 Level LBP

- Sampling points = 8개
- LBP values range = 0 ~ 255 → 256 Level LBP
Uniform Patterns Examples

Non-Uniform Handling

- Non-Uniform Handling \( \rightarrow \) 59-Level LBP
  - 58 uniform LBP: assign each with an unique index (from 0 to 57)
  - 198 non-uniform LBP: assign all with index 58.
Uniform Patterns Examples

LBP Histogram Formation

• Gather statistics of LBP occurrence in a form of histogram

• $B$ = block (1 region)
Example of a Result Using LBP

- Feature Extraction with LBP
  - Advantage: Robust for illumination changes

Texture images obtained by LBP under different lighting conditions
Face Description with LBP
Feature Extraction Using LBP

- **Step 1**: facial image is divided into local regions (blocks). \{R0, R1, ..., Rm-1\} (pixel-level locality)
- **Step 2**: Extract LBP histogram for each region. (regional-level locality)
- **Step 3**: Concatenated all histograms into a spatially enhanced histogram with length of m x n (n is length of a single LBP histogram). (global-level locality)
Feature Matching with LBP

• Dissimilarity measure of Feature matching
  ▪ Specific facial features (such as eyes) contain more important information
  ▪ Be weighted based on the importance of information
    • Chi square distance is utilized ($\chi^2$ measure)
    • $x$ and $\xi$ = normalized enhanced histograms
    • $i =$ histogram index
    • $j =$ local region index
    • $\omega_j =$ weight of region $j$

\[ \chi_w^2(x, \xi) = \sum_{j,i} w_j \frac{(x_{i,j} - \xi_{i,j})^2}{x_{i,j} + \xi_{i,j}}, \quad \text{(Equation 1)} \]

Fig. 4. (a) A facial image divided into $7 \times 7$ windows. (b) The weights set for the weighted $\chi^2$ dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0, and white 4.0.
Experiments Analysis
Experimental Setup

Face recognition system & Database

- Using the Colorado State University Face Identification Evaluation System (CSU System) with images from the FERET database.

- FERET database contains a large number of face images, and the photos of the same person have different expressions, lighting, posture and age.

FERET Database
Experimental Setup

Database Setting

• 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.
  - 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.
Parameters of the LBP Method

- Some parameters can be chosen to optimize the performance of the LBP-based algorithm.
  - Choosing the type of the LBP operator
    - The LBP\textsubscript{u2} operator was selected.
  - Division of the images into regions \( R_0, \ldots, R_{m-1} \)
    - 18*21 pixel windows was selected.
  - Selecting the distance measure for the nearest neighbor classifier
    - the \( \chi^2 \) measure was chosen to be used
  - Finding the weights \( \omega_j \) for the weighted \( \chi^2 \) statistic (Equation 1)

\[
\text{LBP}^\text{u2}_{P,R}
\]
- \( P \) = the number of sampling points, \( R \) = radius
- \( u2 \) = using only uniform patterns
Comparing LBP to Others Local Descriptors

<table>
<thead>
<tr>
<th>Method</th>
<th>fb</th>
<th>fc</th>
<th>dup I</th>
<th>dup II</th>
<th>lower</th>
<th>mean</th>
<th>upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference histogram</td>
<td>0.87</td>
<td>0.12</td>
<td>0.39</td>
<td>0.25</td>
<td>0.58</td>
<td>0.63</td>
<td>0.68</td>
</tr>
<tr>
<td>Homogeneous texture</td>
<td>0.86</td>
<td>0.04</td>
<td>0.37</td>
<td>0.21</td>
<td>0.58</td>
<td>0.62</td>
<td>0.68</td>
</tr>
<tr>
<td>Texton Histogram</td>
<td><strong>0.97</strong></td>
<td><strong>0.28</strong></td>
<td><strong>0.59</strong></td>
<td><strong>0.42</strong></td>
<td><strong>0.71</strong></td>
<td><strong>0.76</strong></td>
<td><strong>0.80</strong></td>
</tr>
<tr>
<td>LBP (nonweighted)</td>
<td>0.93</td>
<td>0.51</td>
<td>0.61</td>
<td>0.50</td>
<td>0.71</td>
<td>0.76</td>
<td>0.81</td>
</tr>
</tbody>
</table>

- **Conclusion**
  - They are robust with respect to variations of facial expressions.
  - Other methods do not survive changes in illumination than LBP.

- **Why LBP has better performance?**
  - LBP is tolerance to lighting changes.
  - No gray-scale normalization is needed prior to apply
  - Highly discriminative
  - Computationally efficient
## Results for the FERET Database

### TABLE 2
The Recognition Rates of the LBP and Comparison Algorithms

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

### Recognition Results
- LBP yields clearly higher recognition rates than other algorithms.
- Especially with weighting, the LBP based description is robust to challenges caused by lighting changes or aging of the subjects.
Results for the FERET Database

Rank Curves

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.
Results for the FERET Database

Robustness of the Method to Face Localization Error

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

![Graph showing recognition rate vs. localization error](image)

Fig. 6. The recognition rate for the f0 set of two LBP-based methods and PCA MahCosine as a function the standard deviation of a simulated localization error.

• Conclusions
  • When no error or only a small error is present, LBP with small local regions works well.
  • As the localization error increases, using larger local regions produces better recognition rate.
  • The recognition rate of the local region based methods drops significantly slower than that of PCA.
Further Work Using LBP-Based Face Description

- Our method has already attained an established position in face analysis research
  - “A Discriminative Feature Space for Detecting and Recognizing Faces”
    [A. Hadid (Oulu Univ.) et al./IEEE CVPR 2004]
  - “Facial Expression Recognition with Local Binary Patterns and Linear Programming”
    [X. Feng (Northwestern Polytechnic Univ.) et al./Pattern Recognition 2005]
  - “Robust Facial Expression Recognition Using Local Binary Patterns”
    [C. Shan (London Univ.) et al./ IEEE ICIP 2005]
  - “Boosting Local Binary Pattern (LBP)-Based Face Recognition”
    [G. Zhang (London Univ.) et al./ Advances in Biometric Person Authentication 2004]
  - “Highly Accurate and Fast Face Recognition Using Near Infrared Images”
    [S.Z. L (Chinese Academy of Sciences) et al./ Int’l Conf. Advances in Biometrics 2006]
  - “Local Gabor Binary Pattern Histogram Sequence (LGBPHS): A Novel Non-Statistical Model for Face Representation and Recognition”
    [W. Zhang (Harbin Institute of Technology Univ.) et al./ IEEE ICCV 2005]
  - “Face Authentication Using Adapted Local Binary Pattern Histograms”
    [Y. Rodriguez and S. Marcel, (IDIAP Research Institute)/ ECCV 2006]
Conclusions

• We proposed a novel and efficient facial representation.

• The recognition rates of our method pretty good than other comparison algorithm presented in this paper.

• Our method has already attained an established position in face analysis research and many research group already study about it.

• Our method has been widely used in different applications such as texture classification, image retrieval, etc.
Future Work

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

• Looking for image preprocessing methods and descriptors that are more robust against image transformations that change the appearance of the surface texture.
Appendix A. CSU System

The parts of the CSU face recognition system

1. Preprocess images;
2. If needed, the algorithm is trained using a subset of the images;
3. The preprocessed images are fed into the experimental algorithm which outputs a distance matrix containing the distance between each pair of images;
4. Using the distance matrix and different settings for gallery and probe image sets, the system calculates rank curves for the system

“Face Recognition with Local Binary Patterns” [T. Ahonen (University of Oulu) et al. /ECCV 2004]
Appendix B. Dissimilarity Measures

• Several possible dissimilarity measures for histograms
  ▪ Histogram intersection:

  \[ D(S, M) = \sum_i \min(S_i, M_i) \]

  ▪ Log-Likelihood statistic:

  \[ L(S, M) = -\sum_i S_i \log M_i \]

  ▪ Chi square statistic\((\chi^2)\):

  \[ \chi^2(S, M) = \sum_i \frac{(S_i - M_i)^2}{S_i + M_i} \]

“Face Recognition with Local Binary Patterns”
[T. Ahonen(University of Oulu) et al. /ECCV 2004]
Appendix C. Dissimilarity Measures Selection

- The performance of the histogram intersection, log-likelihood and $\chi^2$ dissimilarity measures using different window sizes and LBP operators.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Window size</th>
<th>$P(HI &gt; LL)$</th>
<th>$P(\chi^2 &gt; HI)$</th>
<th>$P(\chi^2 &gt; LL)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBP$^{u2}_{8,1}$</td>
<td>18x21</td>
<td>1.000</td>
<td>0.714</td>
<td>1.000</td>
</tr>
<tr>
<td>LBP$^{u2}_{8,1}$</td>
<td>21x25</td>
<td>1.000</td>
<td>0.609</td>
<td>1.000</td>
</tr>
<tr>
<td>LBP$^{u2}_{8,1}$</td>
<td>26x30</td>
<td>0.309</td>
<td>0.806</td>
<td>0.587</td>
</tr>
<tr>
<td>LBP$^{u2}_{16,2}$</td>
<td>18x21</td>
<td>1.000</td>
<td>0.850</td>
<td>1.000</td>
</tr>
<tr>
<td>LBP$^{u2}_{16,2}$</td>
<td>21x25</td>
<td>1.000</td>
<td>0.874</td>
<td>1.000</td>
</tr>
<tr>
<td>LBP$^{u2}_{16,2}$</td>
<td>26x30</td>
<td>1.000</td>
<td>0.918</td>
<td>1.000</td>
</tr>
<tr>
<td>LBP$^{u2}_{16,2}$</td>
<td>32x37</td>
<td>1.000</td>
<td>0.933</td>
<td>1.000</td>
</tr>
<tr>
<td>LBP$^{u2}_{16,2}$</td>
<td>43x50</td>
<td>0.085</td>
<td>0.897</td>
<td>0.418</td>
</tr>
</tbody>
</table>

"Face Recognition with Local Binary Patterns" [T. Ahonen(University of Oulu) et al. /ECCV 2004]

- Histogram intersection and $\chi^2$ measures are clearly better than log-likelihood when the average number of labels per histogram bin is low.
- Log-likelihood performs better when this number increases.
- The $\chi^2$ measure performs slightly better than histogram intersection.