Application of Local Binary Patterns to Face Recognition Problem Solving

Vladimir Petruk,
BMSTU,
Chair of Biomedical Technical Systems

Face recognition problem

Facial recognition system is a computer application for automatically verifying or identifying a person from a digital image.

The verification or identification process may be divided into four basic steps:

- registration and normalization of face image;
- selection of features;
- evaluation of similarity measure;
- decision making.

Main objectives

Main objectives of the work are the development and analysis of facial recognition system based on local binary patterns (LBP).

Subgoals:

- construction of the feature vector;
- selection of the similarity measure;
- construction of the decision rule;
- testing and comparing different approaches.

Local Binary Patterns

LBP – is a type of feature used for classification in computer vision.

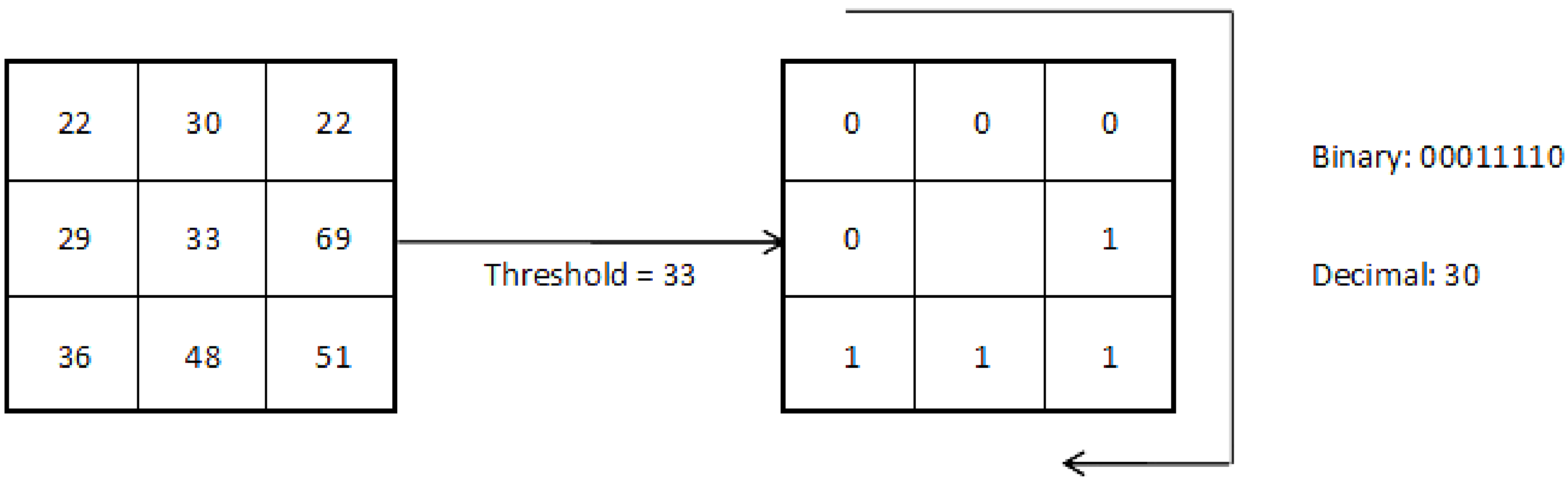

Fig.1. Basic LBP operator

Local Binary Patterns

Using circular neighborhoods and bilinear interpolating the pixel values allow any radius R and number of pixels P in the neighborhood.

A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa. For example, 00000000, 001110000 and 11100001 are uniform patterns.

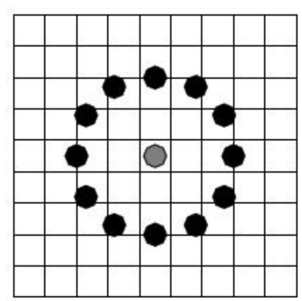

Fig.2. Extended LBP operator

Local Binary Patterns

Uniform LBP

- determine only important local textures, such as ends of lines, edges, angles, spots;
- provides the economy of memory (only $P(P-1)+2$ patterns instead of 2^P).

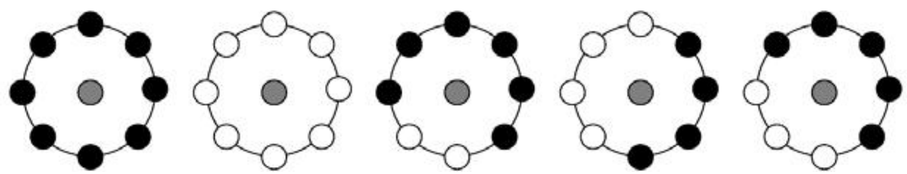

Fig.3. Examples of texture primitives which can be detected by LBP

Face description with LBP

Basic methodology:

- face image is divided into regions;
- histogram of LBP is computed for each region;
- final description of each face is a set of local histograms.

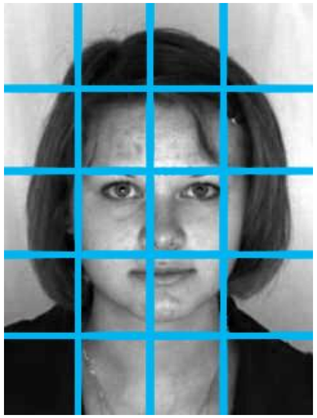

Fig.4. Facial image divided into sub-regions

Template matching

First approach

Symmetrical form of Kullback-Leibler divergence:

$$D = \sum_{i,j} w_{ij} \sum_{k=1}^{P(P-1)+3} log \frac{S_k^1}{S_k^2} (S_k^1 - S_k^2),$$

where *(i,j)* – sub-region's indices, w_{ij} – sub-region's weight, S^1, S^2 – LBP histograms, *k* – LBP histogram column number, *P* – number of pixels in the neighborhood.

Template matching

Second approach

Mahalanobis distance:

$$d(x, y) = \sqrt{(x - y)^T S^{-1} (x - y)},$$

where *x*, *y* – random vectors of the same distribution with the covariance matrix *S*.

Template matching

Third approach
Fisher's linear discriminant (FLD):

$$J(\varphi) = \frac{\varphi^T S_B \varphi}{\varphi^T S_W \varphi} \to max,$$

$$S_B = \frac{1}{N} \sum_{i=1}^{2} N_i (\mu_i - \mu)(\mu_i - \mu)^T,$$

$$S_W = \frac{1}{N} \sum_{i=1}^{2} \sum_{j=1}^{N_i} (x_{ij} - \mu_i)(x_{ij} - \mu_i)^T,$$

$$S_W^{-1} S_B e_k = \lambda e_k,$$

where μ_i – the *i*–th class mean, μ – general mean, N_i – number of samples in the *i*–th class, x_{ij} – sample.

The experiment description

Database: ColorFERET.

Training set: 100 persons, 5 photos per person.

Testing set: 329 persons, 2 photos per person.

False acceptance rate (FAR): 0,1%.

LBP operator: $P = 8$, $R = 2$.

Number of image sub-regions: 6 x 6 (along *x* and *y* axes respectively).

The experiment description

Image preprocessing: median filter, Gaussian filter, cropping, rotation and scaling (120 pixels between the eyes).

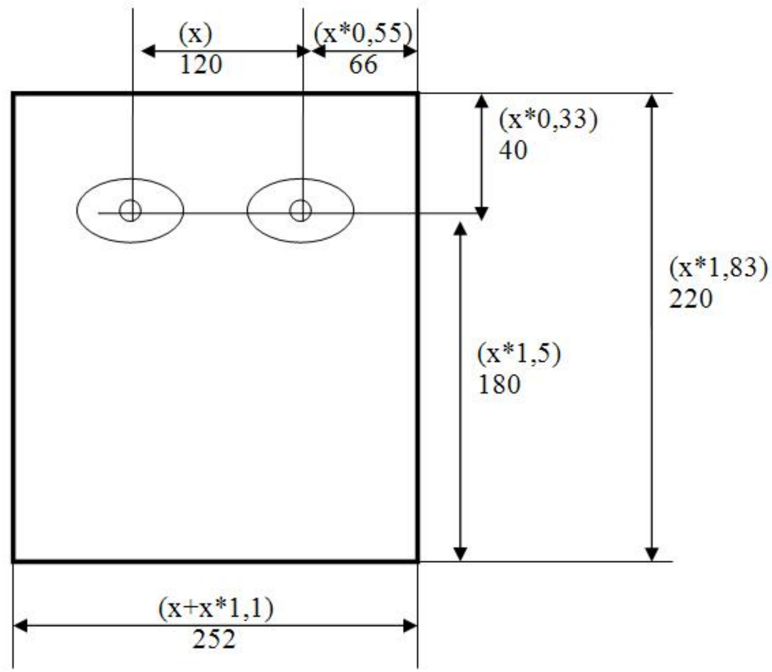

Fig.5. Image normalization parameters

The results of the experiment

Distance	Closed-set identification	Verification
Weighted Kullback-Leibler divergence	89,5 %	84,2 %
Mahalanobis	89,8 %	80,8 %
FLD	92,0 %	86,0 %