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Application of Local Binary Patterns to Face Recognition Problem Solving

Final Report by

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Chapter 1

Introduction

1.1 Facial Recognition Systems

A facial recognition system is a computer application for automatically verifying or identifying a person from a digital image or a video frame from a video source. It is often used in security systems. There are many difficulties during face recognition such as changes in illumination, head rotation, age-related changes and others.

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

1. registration and normalization of face image;
2. selection of features;
3. evaluation of similarity measure;
4. decision making.

1.2 Objectives of the work

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

1. construction of the feature vector;
2. selection of the similarity measure;
3. construction of the decision rule;
4. testing and comparing different approaches.

Chapter 2

Local Binary Patterns

Local Binary Pattern (LBP) is a type of feature used for classification in computer vision. LBP were first suggested in 1996 for analysis of texture of gray-scale images. LBP were found to be invariant by small changes of illumination condition and small rotations [1].

2.1 Basic LBP operator

LBP represent the description of pixel vicinity image in the binary form. Basic LBP operator uses eight pixels of vicinity, accepting the central pixel as a threshold (see Figure 2.1). Pixels with the values, higher than the central one (or equal to it), accept the value <1>, those which are lower than the central one, accept the value of <0>. Thus, we get the eight-bit binary code, which describes the pixel vicinity [1].

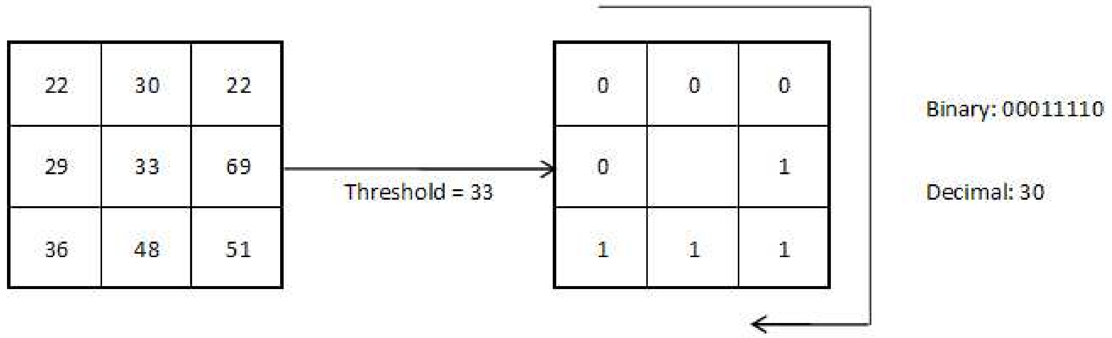

Figure 2.1: Basic LBP operator

2.2 Extended uniform LBP operator

Using circular neighborhoods and bilinear interpolating the pixel values allow any radius R and number of pixels P in the neighborhood (see Figure 2.2) [1-4].

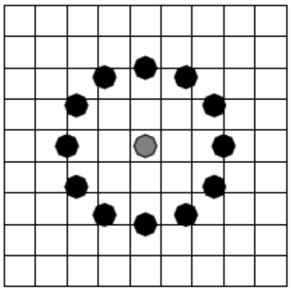

Figure 2.2: Extended LBP operator

Certain binary codes contain more information than others. 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, 001111000 and 11100011 are uniform patterns. Thus, it is possible to use only a subset of all Local Binary Patterns ($P(P-1)+2$ patterns instead of 2^P) to describe the texture of images.

Uniform LBP determine only important local textures, such as ends of lines, edges, angles, spots (see Figure 2.3). Also it provides the economy of memory.

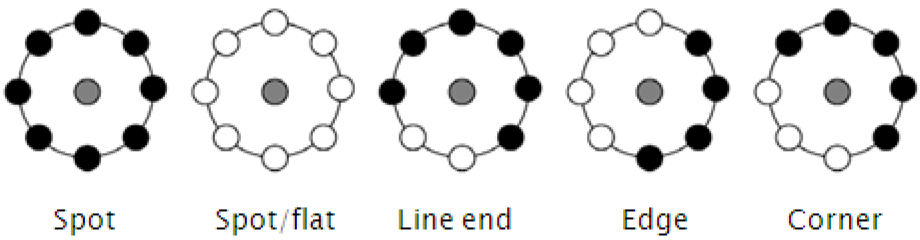

Figure 2.3: Examples of texture primitives which can be detected by LBP

Chapter 3

Face Description with LBP

We can construct LBP histogram by calculating LBP code for each image pixel. Each uniform LBP code corresponds to separate column of histogram. One more column in the histogram corresponds to all LBP codes, which are not uniform.

Face images can be seen as a composition of micro-patterns which can be effectively described by the LBP histograms. A LBP histogram computed over the whole face image encodes only the occurrences of the micro-patterns without any indication about their locations. To also consider shape information of faces, face images were equally divided into small sub-regions to extract LBP histograms (see Figure 3.1). The LBP features extracted from each sub-region are concatenated into a single, spatially enhanced feature histogram. The extracted feature histogram represents the local texture and global shape of face images. Since some regions of faces may take more important information then other regions, it is possible to assign weight to each region, depending on its importance for recognition [2,3]. For example, weights can be obtained by using Student's t-test for the set of training images.

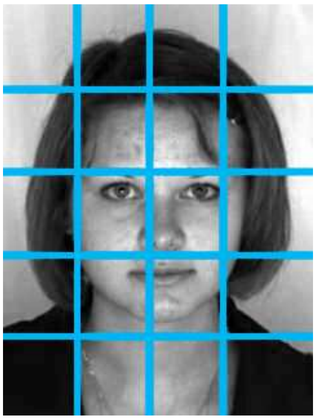

Figure 3.1: Facial image divided into sub-regions

Some parameters can be optimized for better feature extraction. One is the LBP operator, and the other is the number of image sub-regions.

Chapter 4
Template Matching

We have implemented several approaches to compare images using LBP histograms.

4.1 Symmetrical form of Kullback-Leibler divergence

We used the symmetrical form of Kullback–Leibler divergence (4.1) as the dissimilarity measure for histograms.

$$D = \sum_{i,j} w_{ij} \sum_{k=1}^{P(P-1)+3} log \frac{S_k^1}{S_k^2} (S_k^1 - S_k^2), \tag{4.1}$$

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.

Thus, the identification problem can be solved by using nearest-neighbor classifier. The verification problem can be solved by using some threshold value.

4.2 Mahalanobis distance

The second approach is to use the Mahalanobis distance:

$$d(x, y) = \sqrt{(x - y)^T S^{-1} (x - y)}, \tag{4.2}$$

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

The covariance matrix S can be obtained by using set of training images. Also, we can obtain vectors of intrapersonal and extrapersonal differences by using Kullback-Leibler divergence for corresponding sub-regions of each pair of images in the training set. The result is two sets of vectors which represent two classes. So we can calculate mean vector for each class.

In practice, for any pair of images we can obtain the vector of differences. After we can calculate Mahalanobis distances between this vector and mean vectors. The identification and verification problems can be solved by comparing these two distances.

4.3 Fisher's linear discriminant

Next way is to use Fisher's linear discriminant:

$$
\begin{gathered}
J(\varphi) = \frac{\varphi^T S_B \varphi}{\varphi^T S_W \varphi} \to max, \\
S_B = \frac{1}{N} \sum_{i=1}^{2} N_i (\mu_i - \mu)(\mu_i - \mu)^T, \\
S_W = \frac{1}{N} \sum_{i=1}^{2} \sum_{j=1}^{N_i} (x_{ij} - \mu_i)(x_{ij} - \mu_i)^T, \\
S_W^{-1} S_B e_k = \lambda e_{k,}
\end{gathered}
\tag{4.3}
$$

where $\mu_i -$ the i-th class mean, $\mu -$ general mean, $N_i -$ number of samples in the i-th class, $x_{ij} -$ sample.

There are two sets of vectors which represent two classes. The eigenvector corresponding to the largest eigenvalue defines the transformation to the 1-dimension space. The identification and verification problems can be solved in a manner similar previous approach, but we use the transformation to the 1-dimension space instead of calculating Mahalanobis distance.

Chapter 5

Test Results

5.1 The experiment description

For training and testing ColorFERET database was used. All algorithms were trained to provide the false acceptance rate equal to zero point one percent.

Database: ColorFERET.
Training set: 100 persons, 5 photos per person.
Testing set: 329 persons, 2 photos per person.
False acceptance rate (FAR): 0.1%.

The best results were obtained with LBP parameters and image sub-regions number listed below.

LBP operator: $P=8, R=2$.
Number of image sub-regions: 6×6 (along x and y axes respectively).

Median and Gaussian filters were used to reduce noise. Also each image was rotated, scaled and cropped as shown in figure 5.1.

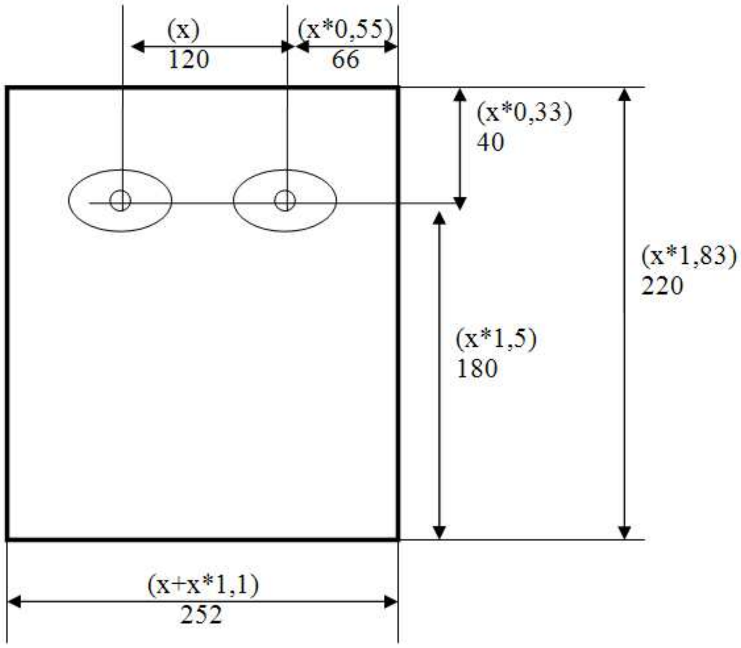

Figure 5.1: Image normalization parameters

5.2 The results of the experiment

The results of the experiment are shown in the table 5.1.

Distance	**Closed-set identification**	**Verification**
Weighted Kullback–Leibler divergence	89.5 %	84.2 %
Mahalanobis	89.8 %	80.8 %
FLD	92.0 %	86.0 %

Table 5.1: The results of the experiment

Chapter 6

Conclusions

In this paper we have briefly described a method for constructing feature vector using local binary patterns.

We have shown that using the same feature vectors, but different decision rules can improve the performance of facial recognition systems. As shown in the table 5.1 the best result was obtained by using Fisher's linear discriminant.

Also, the performance of the system depends significantly on the image preprocessing. Thus, during the work we noticed that without the stage of normalization and noise filtering we have much lower identification and verification rates.

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