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Learning Modified CS-LBP for Face Recognition

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Abstract: The face of a human being conveys extensive information about the identity and emotional state of the person. However, the most important phase in face recognition is extraction. In which the most useful and unique features of the face image are extracted. The Center-Symmetric Local binary Pattern (CS-LBP) feature can be viewed a combination of the texture-based feature and the gradient-based feature. However, due to the low spatial support, the bit-wise comparison made between two single pixel values is significantly affected by noise and is sensitive to image translation and rotation. To address this problem, a modified feature called Multi-scale block Center-Symmetric Local Binary Pattern called as (MCS-LBP) is presented. Instead of pixels, in MCS-LBP the comparison is based on the sum of values of each block’s sub-regions.

Keywords: Face recognition, Center-Symmetric Local binary Pattern (CS-LBP), Multi-scale block Center-Symmetric Local binary Pattern (MCS-LBP)

1 Introduction

Face recognition is used to identify or verify a person using biometric parameters. This process mainly consists of three phases: they are face representation, feature extraction and classification. However, the most important phase is extraction, in which unique features of the face image are extracted. Heikkilä introduced the Center-Symmetric Local binary Pattern (CS-LBP) operator in [1], which combines the good properties of SIFT and LBP, making it effective as a region descriptor. In [1], moreover, features calculated in the local 3x3 neighborhood could capture larger scale structures (macrostructures) that may be dominant features of faces. Therefore, a novel representation using Multi-scale block CS-LBP (MCS-LBP) is proposed to overcome the limitations of CS-LBP. In the modified CS-LBP, we compare average gray values of sub-regions instead of individual pixels.

2 Multi-scale Block Centre-Symmetric Local Binary Pattern

In CS-LBP, instead of comparing the neighboring pixels, the center-symmetric pairs of pixels are compared; however, comparison based on pixel level is significantly affected by noise and sensitive to image translation and rotation. In MCS-LBP, the comparison between single pixels in CS-LBP is replaced with a comparison between

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average gray values of sub-regions. Each sub-region is a square block containing neighboring pixels. We take the side length L of the block as a parameter, and the computational process can be expressed in Equation 1.

Where 'g' is the gray value of individual pixels and B is the sum of the nth value,

After calculating the sum of the pixels of the blocks, computed center-symmetric pairs of blocks (B) are compared, such as (B_0,B_4), (B_1,B_5), (B_2,B_6), and (B_3,B_7) In order to simplify the computation, we use the sum instead of average of gray values of each sub-region. A 3x3 MCS-LBP detailed procedure is explained in Fig. 1. (1)

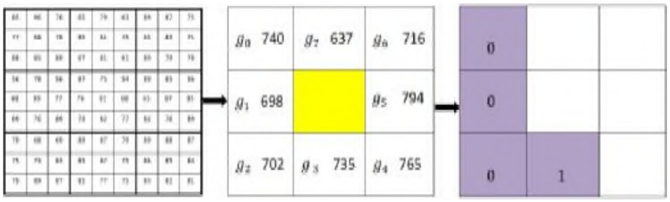

Fig. 1. The MCS-LBP operator. (a) The original 3x3 gray values. (b) Computation of the sum of gray values of each block. (c) Comparison of center-symmetric pairs of pixels and derivation of MCS-LBP code.

Further processing is needed for classification of point of view [2]. In this paper, Chi-square Distance (X2) is delicately used. This has been successfully used for texture and face classification, near-image identification, local descriptors matching, shape classification, and boundary detection. It is defined as follows:

Fig. 2. MCS-LBP filtered images with different scales: (a) Original image, (b) Filtered image by 3x3 , (c) Filtered image by 9x9 MCS-LBP , and (d) Filtered image by 15x15x3 MCS-LBP operators.

$$\chi^2(x,y) = \frac{1}{2}\sum\frac{(x_i - y_i)^2}{(x_i + y_i)} \qquad (2)$$

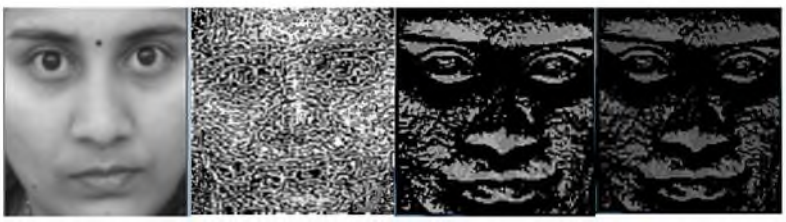

Fig. 3. Histogram extraction for 15 x 15 regions.

To build the system, we collected 600 images from nearly 30 persons a database. So The database included frontal and near frontal views of a person.

Fig. 4. Examples of face images from the face database considered in the experiments.

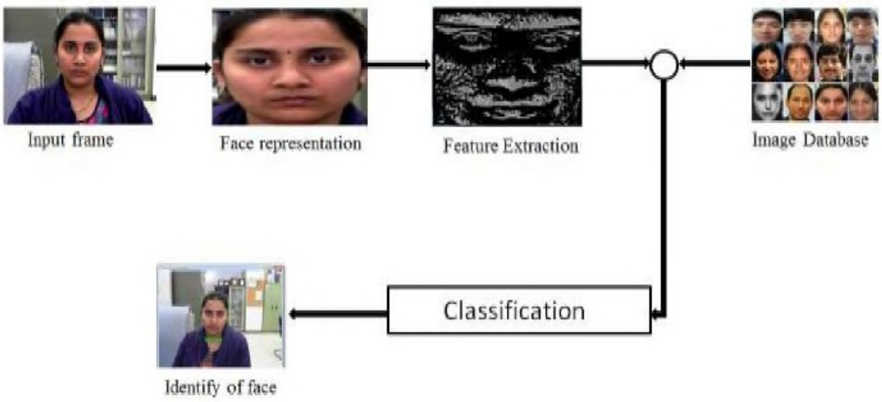

Fig. 5. Step-by-step process of system

Table 1. Recognition accuracy of proposed method compared with other methods

Method	Accuracy (%)
LBP	88.7
CS-LBP	92.8
MCS-LBP	96.3

3 Conclusion

In this paper, MCS-LBP based operator for robust image representation was presented. In the MCS-LBP, the comparison between single pixels in CS-LBP was replaced with a comparison between average gray values of sub-regions and added threshold T was added to the operator. MCS-LBP significantly outperformed the LBP and CS-LBP methods.

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