

Face Recognition using Local Derivative Pattern Face Descriptor

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Abstract

Face detection and recognition is becoming increasingly important in context of surveillance, credit card fraud detection, assistive devices for visual impaired, etc. There are multiple cues available and can be used as features. It has been observed that local features perform better than global cues. Local binary pattern and local derivative pattern try to encode directional pattern of a face image. Hence it becomes important to critically evaluate the performance of LBP and LDP for rotated and scaled faces. Facial features are extracted and compared using support vector machine classification algorithm. We have considered standard databases containing the rotated faces. Also, we have created a database of annotated rotation angle to find out the permissible degree of rotation for LBP and LDP.

Keywords

Local Derivative Pattern, Local Binary Pattern, Support Vector Machine, Face Recognition, Rotation, Scaling

1. Introduction

Face recognition is been a long time favorite research topic for the computer vision people. Many heuristics pattern recognitions strategies proposed to achieve an accurate solution. Over the decades of research its now getting matured and been used in real life applications under the given constrains. The adaptation of the technology by commercial applications is playing major roles in context of surveillance, fraud investigations, biometric authentications etc. The face recognition problem is made difficult by the great variability in head rotation and tilt, lighting intensity and angle, facial expression, aging, partial occlusions (e.g. Wearing Hats, scarves, glasses), etc.

Various methods have been proposed in order to improve the results. Among the feature based methods color, gradients, texture etc. are used mostly. These cues can be used in a local or even in a global fashion. In recent times lot of work has proven the importance of local cues in recognition task. Even after so many decades of work, people are a bit reluctant to use face recognition in mainstream. Hence it becomes critically important to evaluate the recognition algorithms from a real life adaptation viewing points. We propose a framework to

evaluate the local derivative pattern and local binary pattern for rotated and scaled faces. The framework uses the standard databases and also creates the suitable database to achieve the granularity.

The remaining paper is organized as follows. Section II explains the high order local derivative pattern as well as local binary pattern in detail. Section III explains the need of performance evaluation of LBP and LDP under rotation and scale. Section IV explains the details of the experiment. Section V discusses the results in detail whereas conclusions and future work is explained in last section VI. It's been followed by some references.

2. High Order Derivative Pattern

This section explains the local binary pattern and local derivative pattern in detail.

2.1 Local Binary Pattern

Local Binary Pattern (LBP) was introduced by Timo ojala ^[1]. LBP is gradient based local gray scale texture measure and used to model the texture of an image. The original LBP operator labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the value of the central pixel. The binary results of all 3x3 pixels are concatenated to generate a binary string. The decimal equivalent value of this binary string is LBP of the given pixel.

Let Z_0 be the central pixel and Z_1 to Z_8 be the pixels around the central pixel as shown in Fig. 1.

Z_1	Z_2	Z_3
Z_8	Z_0	Z_4
Z_7	Z_6	Z_5

Fig 1: 3x3 neighborhoods around Z_0

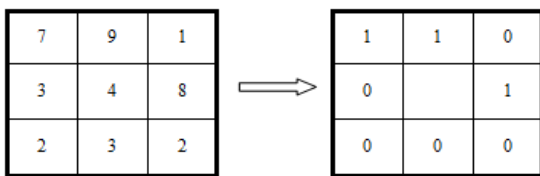
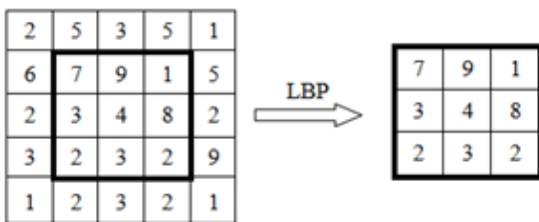
Now, a thresholding function $f(\dots)$ can be defined as

$$f(I(Z_0), I(Z_i)) = \begin{cases} 0, & I(Z_i) < I(Z_0) \\ 1, & I(Z_i) \geq I(Z_0) \end{cases} \quad (1)$$

Where $i = 1, 2, 3, \dots, 8$

Fig 2 shows an example of the LBP where value of central pixel is used as a threshold. A normalized histogram can optionally be calculated and used as the features. The histogram contains the information about the edges and spread of the discontinuities over the image.

LBP is very efficient in terms of computational speed and complexity. Also the memory requirements of LBP are very less. LBP has been proved to be very useful in many of the studies [2]. LBP is very popular due to easy to compute features and used in many face recognition applications.



Pattern = 11010000

$$\text{LBP} = 1 \times 2^0 + 1 \times 2^1 + 0 \times 2^2 + 1 \times 2^3 + 0 \times 2^4 + 0 \times 2^5 + 0 \times 2^6 + 0 \times 2^7 = 11$$

Fig

2: Illustration of basic LBP operator for the region highlighted in black

2.2 Local Derivative Pattern

Local Derivative Pattern was proposed by Baochang Zhang [3] for face recognition with high order local pattern descriptor. It encodes directional feature pattern based on local derivative variations. It can capture more detailed information than the first order LBP. LDP is a micro pattern representation which can also be modeled by histogram to preserve the information about the distribution of the LDP micro patterns. LBP is always considered first-order local pattern operator, because LBP encodes all-direction first-order derivative binary result

whereas LDP encodes the higher-order derivative information. So it contains more discriminative features than LBP see fig. 3.

Given an image, the first-order derivatives along $0^\circ, 45^\circ, 90^\circ$ and 135° directions are denoted as $I'_\alpha(Z)$ where, $\alpha = 45^\circ, 90^\circ$ and 135° . Let Z_0 be a point in $I(Z)$, and $Z_i, i = 1, \dots, 8$ be the neighboring point around Z_0 (see Fig. 1). The four first-order derivatives at $Z = Z_0$ can be written as

$$\begin{aligned} I'_{0^\circ}(Z_0) &= I(Z_0) - I(Z_4) \\ I'_{45^\circ}(Z_0) &= I(Z_0) - I(Z_3) \\ I'_{90^\circ}(Z_0) &= I(Z_0) - I(Z_2) \\ I'_{135^\circ}(Z_0) &= I(Z_0) - I(Z_1) \end{aligned} \quad (2)$$

The second order directional derivative in α direction at $Z = Z_0$ can be defined as

$$\text{LDP}_\alpha^2(Z_0) = \{f(I'_\alpha(Z_0), I'_\alpha(Z_1)), f(I'_\alpha(Z_0), I'_\alpha(Z_2)), \dots, f(I'_\alpha(Z_0), I'_\alpha(Z_8))\} \quad (3)$$

Finally, 8-bit LDP can be derived by concatenating the derivatives for all directions.

$$\text{LDP}^2(Z) = \{\text{LDP}_\alpha^2(Z) | \alpha = 0^\circ, 45^\circ, 90^\circ, 135^\circ\} \quad (4)$$

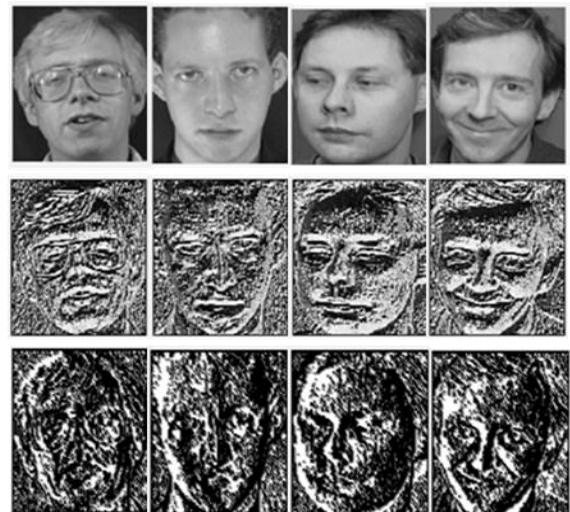


Fig.3: Visualization of LBP and LDP, first row is original images, second row and third row is LBP and LDP of it.

Hence a 32 bit binary number is generated as a result of comparing two derivatives for two neighboring pixels.

LDP can be learned as illustrated in Fig.4. It can be classified as either a 3 point or 4 point template. For a 3 point template assigns a "0" to a monotonically increasing or decreasing pattern and "1" is assigned to turning point. Similarly for a 4 point template a gradient turning pattern is labeled as "1" and monotonically increasing or decreasing pattern is labeled as "0".

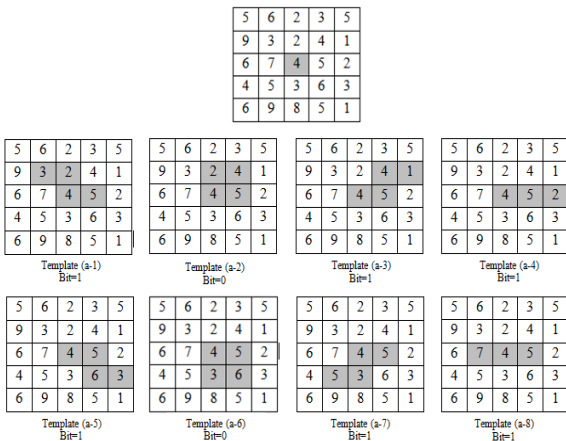


Fig 4: 3 point and 4 point LDP Templates

2.3 High Order Local Derivative Pattern

To calculate the third order LDP, we first calculate the second order LDP along all directions denoted as $I''(Z)$. Hence a third order LDP, $LDP^3_\alpha(Z_0)$ in alpha direction at $Z = Z_0$ can be defined as

$$LDP^3_\alpha(Z_0) = \{f(I''_\alpha(Z_0), I''_\alpha(Z_1)), f(I''_\alpha(Z_0), I''_\alpha(Z_2)) \\ \dots, f(I''_\alpha(Z_0), I''_\alpha(Z_g))\} \quad (5)$$

Finally a 3'rd order LDP can be obtained by concatenating the LDP in all directions.

3. Rotation And Scale

Most of the experiments evaluating face recognition algorithms do not consider rotation and scale factors. However in real life situations this assumption tends to fail. Most of the applications consider a static camera. And assurance of face capturing from same scale can be given. Also in some of active centric applications, camera has to focus to center of the face always. Hence robustness against rotation and scale needs to be evaluated.

The rotation can be assumed of two types' In-plane rotation and multi plane rotation. In case of single plane rotation the face has been rotation along the vertical axis in plane orthogonal to camera optical axis. Whereas in cases of multi plane rotation; a face can be rotated in any of the available planes. Here in this evaluation we will be focusing on in plane rotations only.

Scale is also an important factor while transforming to use any face recognition system from lab to real life. Effect of scale can be learned by capturing multiple images from a static camera from varying distances. The distance will be vertical distance along the optical axis of the camera.

4. Experiment

We conducted several experiments to evaluate performance of LBP and LDP. However very few data sets are available freely, hence data generation needs to be performed. Following sections explain previous experiment, data generation, training methodology and parameter settings used for experimentation.

4.1 Previous Experiments

Previous experiments for LBP and high order LDP are conducted by Zhang et al [3]. The authors extend the LBP and LDP to feature images containing wider range of appropriate discriminative features could achieve a higher level of system performance.

The experiments used a large data from FERET[4], CAS-PEAL[5], CMU-PIE[6], Extended Yale B[7], and FRGC[8] databases. The authors considered LBP, 2'nd order LDP, 3'rd order LDP and 4'th order LDP on gray scale as well as Gabor images. The extensive experiments concluded that 3'rd order LDP performs consistently better using gray scale as well as Gabor images[3].

4.2 Data Generation

There are various data sets available containing faces under various illumination conditions. However annotated database of rotated faces is not available freely. Hence it becomes extremely important to generate a database of faces under various rotations. Commonly available databases are FERET, CAS-PAL, CMU-PIE, Yale B and FRGC.

FERET is a very popular database used for face recognition purpose. It contains the faces under various expressions, lighting conditions and ageing. 'Experiment a' containing 1,196 frontal images of 1,196 subjects was used as the gallery set, while 'Experiment b' (1,195 images with expression variations), 'Experiment c' (194 images taken under different illumination conditions), Dup I (722 images taken later in time between one minute to 1,031 days), and Dup II (234 images, a subset of Dup I taken at least after 18 months) were used as the Probe sets.

CAS – PEAL database have images for various poses and illumination conditions for 1040 subjects. It contains slightly more images than 9000. It focuses on faces having various accessories for different lightning conditions. CAS-PIE database have images for various poses and illuminations. This database contains the face images of 68 subjects. This is the only database suitable for our experimental purpose.

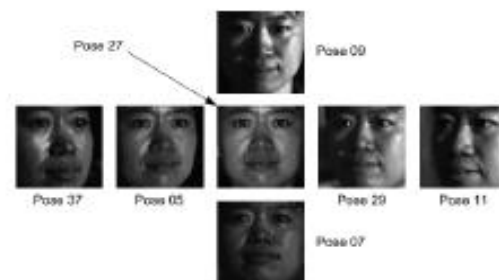


Fig 5: Samples from CAS-PIE database

We used small handheld photography camera to capture the images. We captured 19 images for 17 subjects. First5 images are frontal images, next 5 images has the rotation on left and right side with a delta of 5 degrees. Then we have some images to cater illumination conditions. Finally 5 images were captured at varying distance from the camera starting from 5m with a delta of 1m [8].

4.3 Training Methodology

We used linear Support Vector Machine [9] algorithm for classification purpose. SVM is known as best classifier for face recognitions problem. We used MATLAB implementation of SVM which provides readily available functions for training and testing. Also you have a freedom to configure the parameters. We used single SVM classifier for each person in the database [10]. Training takes lot of time hence database images sub sampled to a common resolution. Average training time required for around 100 images was up to 10 hours using dual core Intel machine running at 2.53 GHz.

5. Results

We primarily categorized entire dataset into training set and test/probe set. Training set is used for learning the SVM classifier and probe set is used for testing purpose. We conducted two experiments; experiment a training set was not containing any rotated faces. Whereas in experiment b, Training set contains some of the rotated faces.

The authors of [3] Zhang et al concluded that 3rd order LDP performs consistently better than LBP and 2nd order LDP. They have covered very large dataset for the experimentation. Also, 3rd order LDP performs better than 4th order LDP. Hence it can be concluded that higher order LDP captures more detailed information than first order LBP and second order LDP. Higher order LDP can be used with gray scale images as well as Gabor feature images. And it has been seen that, Gabor feature images prove to be more accurate than gray scale images. Hence for evaluating for rotation and scale factors, we only use 3rd order LDP features with Gabor feature images.

Also, we have to choose appropriate parameters values for 3rd order LDP. The accuracy of the algorithm highly depends on selection of correct Sub region size and number of histogram bins. We are going to use 11x11 sized sub regions with 64 histogram bins. All images are normalized to 88x88 pixels.

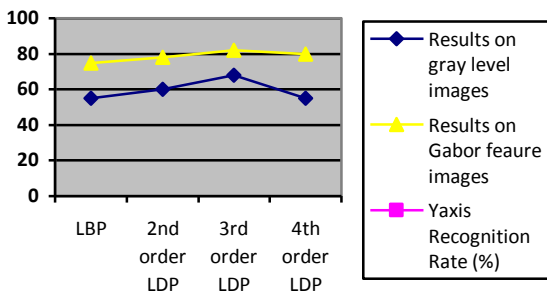


Fig 6: Comparison of accuracies by using various features with the help of CAS-PEAL database [3]

Fig. 6 shows effect of rotation on 3rd order LDP with Gabor feature images.

Experimental data shown in Fig. 7 indicates continuous decrease in accuracy with the degree of rotation. It's aligning with the fact that LDP features are highly oriented features uses texture patterns. These results are for experiment a where rotated faces

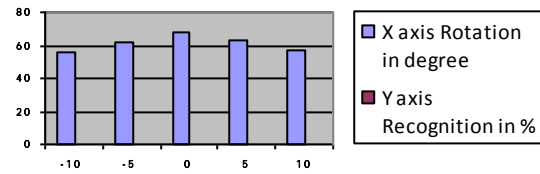


Fig 7: Analysis of Accuracies under various degrees of rotation using generated database using 3rd for experiment 'a'

not present in gallery set. We have used rotated faces as probe images.

The rank one accuracy will rise in case of experiment b where rotated faces are present in the database. Fig. 8 describes the results for experiment b. It can be observed that overall accuracies have gone up when we are using rotated faces in the training data sets. However the average training time shoots up exponentially with the increase in number of training images. There is a tradeoff between training time and accuracy expected. But in any of the cases it is difficult to maintain a good accuracy beyond a certain range of rotation.

Effect of scale is very minimal on the accuracies; a difference of around 5m from the camera is almost negligible. Changing the scale is not changing any directional pattern hence accuracy can be maintained in cases of scale change.

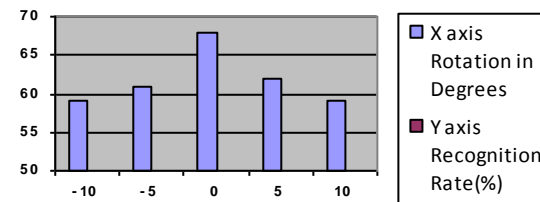


Fig 8: Analysis of Accuracies under various degrees of rotation using generated database using 3rd for experiment 'b'

6. Conclusion And Future Work

This paper evaluates the effect of rotation and scale factors on recognition rate while using 3rd order LDP with Gabor feature images. It can be concluded from experimental data that the effect of rotation works adversely whereas effect of scale has minimum effect. The recognition after a certain degrees of rotation is not possible. Also, experiment shows that permissible range of rotation is -10 degrees to +10 degrees.

The main contribution of this paper includes

- 1) Generation of labeled data for analyzing rotation and scale effect
- 2) Concluding the effect of rotation
- 3) concluding effect of scale.

Need of algorithm to nullify the effect of rotation should be noticed. While using LDP's rotation has to be handled at the level of preprocessing as derivative pattern encrypts the directional relations. The implementation for minimizing the effect of rotation can be considered in future.

7. References

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