Difference-Based Local Gradient Patterns for Image Representation

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Abstract. This paper aims to examine the impact of pixel differences on local gradient patterns (LGP) for representing facial images. Two difference-based descriptors are proposed, namely, the angular difference LGP (AD-LGP) and the radial difference LGP (RD-LGP) descriptors. For evaluation purpose, two experiments are conducted. The first is face/non face classification using samples from CMU-PIE and CBCL databases. The second is face identification under illumination variations using the extended Yale face database B and the CMU-PIE face database. The experimental results show that both descriptors demonstrate, generally, a higher capability in discriminating face patterns from non-face patterns than the standard LGP. However, in face identification, the AD-LGP descriptor shows robustness against illumination variations, while the performance of the RD-LGP descriptor degrades with hard illuminations. Furthermore, we enhance the RD-LGP descriptor using the Average-Before-Quantization (ABQ) approach in order to increase its robustness toward illumination changes.

Keywords: Local gradient patterns · Face identification · Face non-face classification

1 Introduction

Automatic face analysis has the utmost importance in computer vision research, with applications like biometric identification, visual surveillance, information security and access control, human-machine interaction, video conferencing and content based image retrieval. Face analysis includes many topics such as face detection and facial feature extraction, face tracking and pose estimation, face and facial expression, and face modeling and animation [1,6]. What makes the problem of face analysis challenging is the fact that facial appearance varies due to changes in pose, expression, illumination and other factors such as age and make-up [3].

Recently, very discriminative and computationally efficient local texture descriptors have been proposed such as local binary patterns (LBP)[11], which

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has led to a significant progress in applying texture-based methods to different computer vision applications. While texture features have been successfully used in different computer vision problems, only few works have considered them in facial image analysis before the introduction of the LBP [2,5]. Since then, the methodology has inspired a lot of new methods in face analysis, thus revealing that texture based region descriptors can be very efficient in representing and analyzing facial features.

LBP is capable to provide a transformed output image that is invariant to the global intensity variations. However, when LBP is utilized in representing facial features, it is sensitive to local variations that occur commonly along edge components of the human face [7,13]. As such, several extensions of LBP have been proposed with an aim to increase its robustness and discriminative power. Recently, Jun et al. proposed a novel image representation method called local gradient patterns (LGP) generates constant patterns irrespective of local intensity variations [7].

Although LGP is based on calculating the local difference between a pixel and its neighbor pixels, in practice, the calculation of LGP may be affected by some irrelevant situations, for example, varying viewpoint, or local curvature [4]. Local image curvature has many reasons such as illumination variations, edge components, and so on. Motivated by the work of Liu et al. [10], in this paper, we propose two simple, yet powerful difference-based descriptors, generalizing the standard LGP approach. More specifically, we present two descriptors; the angular difference LGP (AD-LGP) and the radial difference LGP (RD-LGP) in angular and radial directions of a circular grid respectively.

As the AD-LGP descriptor is concerned with the angular differences, the most prominent advantage of the AD-LGP is the capability to recover the local curvature cased by illumination variations. Also, AD-LGP is designed to have higher stability with monotonic gray scale transformations at the pixel levels. It considers the gray level differences with a given angular displacement between pairs of evenly spaced pixels on the circular neighborhood, which makes AD-LGP more tolerant with illumination variations.

In a similar way, RD-LGP considers the gray level differences between pairs of pixels of evenly spaced pixels in the same radial direction. Thus RD-LGP is capable to capture the edge information between different circumferences. However, we found experimentally that RD-LGP is sensitive to illumination changes. Thus, we incorporate the Average-Before-Quantization (ABQ) approach [9], in order to enhance the robustness of the RD-LGP descriptor through illumination variations. In this combination, we limit the number of neighboring pixels to be a multiple of four, and then local averaging along an arc is used, such that the number of neighbors is always four.

Two experiments are conducted in order to evaluate the proposed descriptors. The first experiment is face/non face classification problem, using face samples from CMU-PIE database [14] and face/non-face samples from CBCL database [15]. The experimental results demonstrate that both AD-LGP and RD-LGP descriptors have a higher capability, in discriminating face patterns from non-face patterns, than the standard LGP. The second experiment is face identification problem across illumination, using samples form the Extended Yale Face Database B[8] and CMU-PIE Database[14]. The experimental resutls asserts the robustness of the AD-LGP and the enhanced RD-LGP (ERD-LGP) descriptors against illumination variations over the standard LGP.

This paper is organized as follows: Section 2 shows an overview of the standard LGP approach. Also, a description of the proposed descriptors AD-LGP, RD-LGP, and the enhanced ERD-LGP are provided in section 2. Experimental results are shown in section 3. Section 4 shows conclusion and future work of this paper.

2 Proposed Descriptors

2.1 A Brief Overview of Local Gradient Patterns(LGP)

The LGP operator first introduced by Jun et al. [7], uses the gradient values of the eight neighboring pixels of a specified pixel, which are calculated as the absolute values of intensity differences between the specified pixel and its neighboring pixels. Then, the average of the gradient values of the eight neighbors is allocated to the specified pixel and is used as a threshold value for LGP encoding as follows. A pixel is assigned a value of 1 if the gradient value of its neighbor is higher than the threshold; otherwise it is assigned a value of 0. The LGP code for the specified pixel is then obtained by the concatenation of the binary 1s and 0s into a binary code (see Fig. 1). Here, we consider a circular neighborhood of radius r centered on a specified pixel and take p neighboring pixels on the circle. Whenever, the sampling point is not in the center of a pixel, bilinear is necessary (see Fig. 2). The gradient value between a central pixel x_c and its neighbor x_n is set as follows:

$$g_n = |x_n - x_c|\,, \tag{1}$$

where the average of the p gradient values is given as:

$$\bar{g} = \frac{1}{p}\sum_{n=0}^{p-1} g_n \tag{2}$$

Then, the $LGP_{p,r}$ descriptor is defined as:

$$LGP_{p,r} = \sum_{n=0}^{p-1} s\left(g_n - \bar{g}\right) 2^n, \quad s\left(x\right) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \tag{3}$$

Motivated by the coding strategy and properties of LGP we propose the following two different descriptors based on pixel differences in both the radial and angular directions on a circular grid. The proposed descriptors are different from the traditional pixel differences, which are computed in horizontal and vertical directions. In these descriptors, we modified the scheme of comparing pixels in the neighborhood of the standard LGP descriptor.

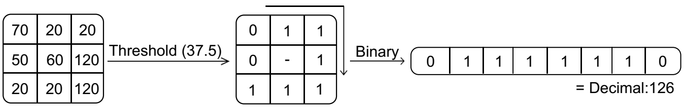

Fig. 1. The original LGP operator

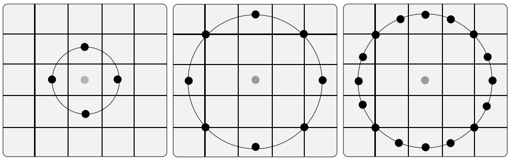

Fig. 2. The circular (4,1), (8,2) and (16,2) neighborhoods

2.2 AD-LGP Descriptor

In this descriptor, instead of calculating the gradient values as the absolute values of the intensity differences between the specified pixel and its neighboring pixels, we use the angular differences with a given angular displacement $\delta(\frac{2\pi}{p})$, where δ is an integer value such that $1 \leq \delta \leq \frac{p}{2}$. Then, the gradient values of the neighbors of the given pixel can be calculated as:

$$\varDelta_{\delta,n}^{Ang} = x_{r,n} - x_{r,mod(n+\delta,p)} \tag{4}$$

where $x_{r,n}$ and $x_{r,mod(n+\delta,p)}$ correspond to the gray values of pairs of pixels of δ evenly spaced pixels on a circle of radius r, and the function $mod(x, y)$ computes x modulus y. The average of the gradient values is set as:

$$\mu = \left(\frac{1}{p}\right) \sum_{n=0}^{p-1} \varDelta_{\delta,n}^{Ang} \tag{5}$$

Furthermore, toward robustness on possible flat image regions we use a small threshold value ε for the sign function (in this paper, we set ($\varepsilon = 0.01$). Then, $AD - LGP_{p,r,\delta,\varepsilon}$ descriptor can be written as, see Fig. 3 for calculation example:

$$AD - LGP_{p,r,\delta,\varepsilon} = \sum_{n=0}^{p-1} s\left(\varDelta_{\delta,n}^{Ang} - \mu\right) 2^n, \quad s(x) = \begin{cases} 0, & x < \varepsilon \\ 1, & x \geq \varepsilon \end{cases} \tag{6}$$

2.3 RD-LGP Descriptor

In the RD-LGP descriptor, the gradient values of a given pixel are computed as the absolute values of the radial differences with a given integer radial displacement δ such that:

$$\varDelta_{\delta,n}^{Rad} = |x_{r,n} - x_{r-\delta,n}| \tag{7}$$

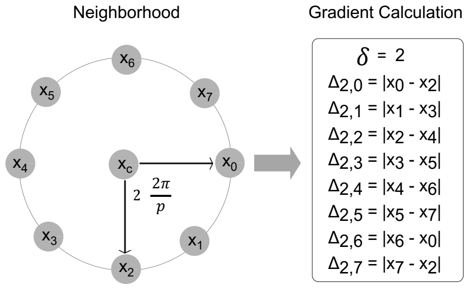

Fig. 3. Illustration of calculating the gradient values for AD-LGP with $\delta = 2$

where $x_{r,n}$ and $x_{r-\delta,n}$ correspond to the gray values of pairs of pixels of δ evenly spaced pixels of the same radial direction as illustrated at Fig. 4. The average value of the gradient values of a given pixel is defined as:

$$\mu = \left(\frac{1}{p}\right) \sum_{n=0}^{p-1} \Delta_{\delta,n}^{Rad} \tag{8}$$

Then, the $RD - LGP_{p,r,\delta}$ descriptor can be expressed as:

$$RD - LGP_{p,r,\delta} = \sum_{n=0}^{p-1} s\left(\Delta_{\delta,n}^{Rad} - \mu\right) 2^n, \quad s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \tag{9}$$

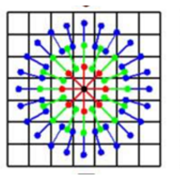

Fig. 4. Illustration of radial differences of pixels

2.4 ERD-LGP Descriptor

During the experiments of this paper, we noticed that RD-LGP outperformed the standard LGP in some situations and degraded in other situation. The degradation in the performance of RD-LGP occurs in case of hard illumination variations. Since the nature of RD-LGP is close, to some extent, to standard LGP, it inherits the sensitivity of LGP to large illumination variations. Then, a further enhancement is needed to increase the robustness of the RD-LGP descriptor against change in illumination conditions.

Thus, we use the Average-Before-Quantization (ABQ) strategy [9] in order to extend the RD-LGP descriptor. The enhanced RD-LGP (ERD-LGP) descriptor

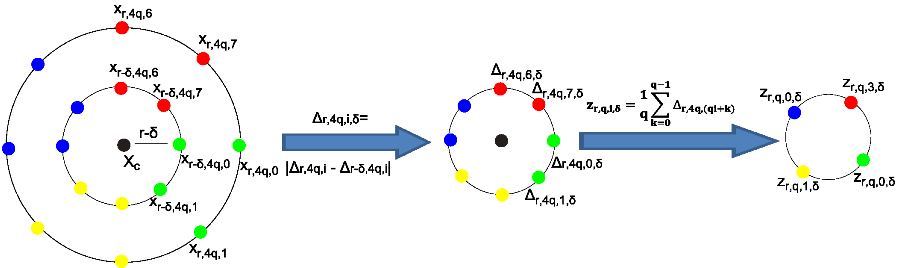

Fig. 5. Illustration of the proposed ERD-LGP descriptor

works as follows: we limit the number of points sampled around the central pixel x_c to be a multiple of the value four, thus $p = 4q$ for a positive integer q. So the neighbors of x_c sampled on the radius r can be gathered in the vector $\mathbf{X}_{r,4q} = [x_{r,4q,0}, ..., x_{r,4q,4q-1}]^T$. Then, we compute the local radial differences as:

$$\varDelta_{r,4q,i,\delta} = |x_{r,4q,i} - x_{r-\delta,4q,i}|\,, \quad i = 0, ..., 4q-1. \tag{10}$$

where $x_{r,4q,i}$ and $x_{r-\delta,4q,i}$ correspond to the gray values of pairs of pixels of δ evenly spaced pixels of the same radial direction. $\varDelta_{r,4q,\delta}$ is transformed into:

$$z_{r,q,i} = (\frac{1}{q}) \sum_{k=0}^{q-1} \varDelta_{r,4q,(qi+k),\delta}, \quad i = 0, .., 3. \tag{11}$$

Then, we compute a binary pattern based on $\mathbf{Z}$ via:

$$ERD - LGP_{p,r,\delta} = \sum_{n=0}^{3} s\left(z_{r,q,n} - \mu^l_{r,q}\right) 2^n, \quad s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \tag{12}$$

where μ^l is the local thresholding value:

$$\mu^l_{r,q} = (\frac{1}{4}) \sum_{n=0}^{3} z_{r,q,n} \tag{13}$$

The construction of the ERD-LGP descriptor is illustrated in Fig. 5.

3 Experiments and Results

In this section we show the experimental results to evaluate the performance of the proposed descriptors; AD-LGP, RD-LGP, and ERD-LGP. The first experiment shows the classification rates of the first two descriptors compared to standard LGP in discriminating face from non-face patterns. The second experiment shows the recognition rates of the three descriptors compared to the standard LGP in discriminating faces of different subjects under variety of illumination conditions. In both experiments, we used the support vector machine (SVM) as a classifier. SVM is a well-founded classifier in statistical learning theory and has been successfully utilized in various classification problems [16].

(a) (b) (c)

Fig. 6. Samples of the images used in training and testing phase (a) CMU-PIE face (b) CBCL face (C) CBCL non-face

3.1 Face/Non-face Classification

Face/Non-face classification problem is one of the essential problems in face analysis domain. It is simple enough to the extent that we can judge fairly the classification power of the proposed approaches. The experiment of face/non-face classification can be used separately or, mostly, is used as a part of overall face detection or face recognition applications.

In the training phase for this experiment, we use 1215 frontal face samples from the CBCL face database, 2142 frontal, right twist, and up tilt face samples from the CMU-PIE database, namely poses 27, 05 and 07, and 4548 non-face samples from the CBCL database. In the testing phase, we use 3486 frontal, right twist and up-down tilt faces from CMU-PIE database, namely poses 27, 05, 07 and 09, including subjects not used in the training set and 10328 non-face samples from the CBCL database. Fig. 6 shows samples of the face and non-face images used in training and testing phases. All training and testing images, from the CMU-PIE database, are manually cropped and resized into a resolution of 19×19 pixels. During experiments, two scenarios are adopted: Scenario #1, we build a holistic description of image where $r = 2$ and $p = 8$ to obtain a 256-bin histogram. Scenario #2, we divide the input image into nine overlapping regions each with 10×10 pixels. From each region, we compute a 16-bin histogram using $r = 2$ and $p = 4$ and concatenate the results into a single 144-bin histogram. In this scenario, we choose p = 4 to avoid statistical unreliability due to long histograms computed over small regions [12]. All the resulted 7905 face and non-face histograms are used to train the SVM. Table 1 shows results of the face/non-face classification problem for both scenarios.

Table 1. Classification accuracy for the proposed descriptors against LGP via the two scenarios

Scenario	LGP	AD-LGP	RD-LGP
#1	93.47%	93.64%	95.98%
#2	92.25%	94.88%	95.48%

As it is shown in Table 1, both the proposed descriptors outperform the standard LGP in the two scenarios. Also, the RD-LGP outperforms both AD-LGP and LGP. It seems that, the scenario #2 is better, for AD-LGP, than scenario #1. In the scope of each descriptor shown in section 2, these results are expected. As long as input image does not include large variations, the radial differences will work better than the angular differences. In the next experiment where illumination is included, the situation will be different, as we will see shortly.

It is clear that, both the proposed descriptors outperform the standard LGP in the two scenarios. Also, the RD-LGP outperforms both AD-LGP and LGP. It seems that, the scenario #2 is better, for AD-LGP, than scenario #1. In the scope of each descriptor shown in section 2, these results are expected. As long as input image does not include large illumination variations, radial differences will work better than angular differences. In the next experiment where illumination varies greatly among samples, the situation will be different, as we will see shortly.

3.2 Face Identification across Illumination

In this experiment, we examine the performance of the standard LGP and the proposed descriptors in discriminating faces of different subjects using two databases; the Extended Yale Face Database B [8] and the CMU-PIE Face Database[14]. The Extended Yale B database, used in this paper, includes 28 subjects under 9 poses $\times$ 60 illumination conditions. Half of the illumination conditions are devoted for training phase, i.e. $(28 \times 9 \times 30 = 7560)$ and the other half is devoted for testing phase, as well. Fig. 7 shows samples of the extended Yale B face database. A subset of the CMU-PIE database containing frontal, right-left twist and up-down tilt images of 67 subjects under 21 illumination condition(7035 in total), is used and 2 fold cross validation is performed in experiment using this database.

In the experiment settings, we choose r =2 and p =4 for the same reason mentioned in previous experiment. All images are manually cropped, resized to 48×48 pixels and divided into 3 overlapping regions each with 19×19 pixels. From each region, we compute a 16-bin histogram and concatenate the results into a single 144-bin histogram for each descriptor. Regarding the SVM classifier, the multi-class face identification problem is reduced into multiple two-class problems (i.e.,$28 \times (28-1)\,, 67 \times (67-1)$) using one-versus-one approach and classification is done by a max-wins voting strategy.

Fig. 7. Samples of the extended Yale B face database

Fig. 8 shows a comparison between performance of the standard LGP from one side and performance of the proposed descriptors from the other side using the extended Yale B database. The performance comparison is conducted across

5 subsets; each includes 6 illumination conditions, according to severity of illumination conditions from moderate to extreme luminance. It is clear that, the AD-LGP descriptor shows a significant improvement in recognition accuracy compared to either LGP or even RD-LGP. The three descriptors start with optimum accuracy, 100%, using subset 1 and subset 2. In case of moderate illumination conditions (subset 3), the three descriptors, show good performance, whereas their performance starts to degrade gradually with severe illuminations (subset 4 and subset 5) with clear superiority for the AD-LGP descriptor over LGP.

Although, the RD-LGP descriptor showed a better performance compared to the AD-LGP descriptor in face/non-face classification, its performance degraded here. Since the nature of the RD-LGP descriptor is close, to some extent, to the standard LGP, it inherits the sensitivity of LGP to large illumination variations. In contrast of previous experiment, the superiority of angular differences over radial differences is reasonable in case of large illumination variations. As computing the pixel differences, in the angular direction increases the capability of the AD-LGP descriptor to recover the local curvature cased by illumination variations.

The enhanced ERD-LGP descriptor shows, less sensitivity to changes in illumination conditions than RD-LGP or LGP itself. This is due to the integration of the circular averaging before quantization strategy, which increases the robustness of the descriptor against illumination changes.

Table 2 shows the performance of the LGP and the proposed descriptor in face identification using the CMU-PIE database. Again results demonstrate the superiority of the AD-LGP descriptor over both LGP and RD-LGP descriptors. However, the ERD-LGP descriptor outperform the AD-LGP descriptor here, as illumination variation in this case is less than in case of the Extended Yale B database.

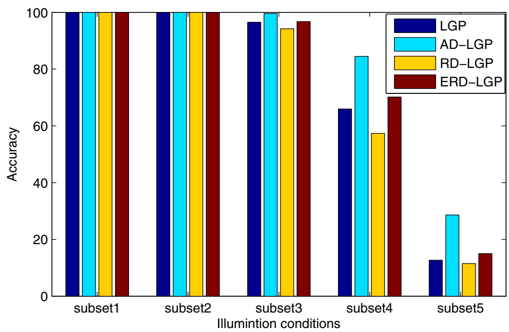

Fig. 8. Comparison between LGP, AD-LGP, RD-LGP and ERD-LGP descriptors performance using the Extended Yale B database

Table 2. Comparison between LGP, AD-LGP, RD-LGP and ERD-LGP descriptors performance using the CMU-PIE

LGP	AD-LGP	RD-LGP	ERD-LGP
81.86%	87.36%	79.98%	90.77%

4 Conclusion and Future Work

This paper proposes an extension to local gradient patterns (LGP) in order to increase its robustness and overall performance. Two difference-based descriptors are presented, namely, the angular difference LGP (AD-LGP) and the radial difference LGP (RD-LGP). Both descriptors are discriminative and showed better performance in face analysis. For evaluation, two experiments are conducted in this paper. The first is a face/non face classification using samples from CMU-PIE and CBCL databases. The second experiment is face identification across illumination, using the Extended Yale face Database B and the CMU-PIE Database.The experimental results showed that both descriptors demonstrate a higher capability in discriminating face patterns from non-face patterns than the standard LGP.

However, in face identification, the AD-LGP descriptor shows robustness against illumination variations, while the performance of the RD-LGP descriptor degrades with hard illuminations. Thus, we enhanced the RD-LGP descriptor using the Average-Before-Quantization (ABQ) strategy, which limits the number of pixels taken around the central pixel to be a multiple of a certain number. This guaranteed to increase the robustness of RD-LGP descriptor toward illumination variations. In future work, we are planning to combine, both AD-LGP and RD-LGP descriptors for a robust image representation. As they capture true complementary texture information, in that the AD-LGP descriptor measures the variations of the neighbors with angular displacement on the same circumference, while the RD-LGP captures the edge information between circumferences.

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