# Dominant LBP Considering Pattern Type for Facial Image Representation

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**Abstract.** Facial image representation plays an important role in computer vision and image processing applications. This paper introduces a novel feature selection method, dominant LBP considering pattern type (DLBP-CPT), capable to capture, effectively, the most reliable and robust dominant patterns in face images. In contrast to the Dominant LBP (DLBP) approach, we take into account the dominant pattern types information. We find that pattern type represents essential information that should be included, especially, in facial image representation across illumination. We apply the proposed method with the conventional LBP and the angular difference LBP (AD-LBP) operators. It is shown in this paper, that the proposed DLBP-CPT and DAD-LBP-CPT descriptors are more reliable to represent the dominant pattern information in the facial images than either the conventional uniform LBP or other dominant LBP approaches.

**Keywords:** Local binary patterns · Facial representation · Feature selection · Face identification

## 1 Introduction

Facial image representation 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 representation is included in 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 representation 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) [12], which has led to a significant progress in applying texture-based methods to


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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 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.

Ideally, 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]. Also, the basic LBP operator generates rather long histograms overwhelmingly large even for a small neighborhood size, leading to poor discriminative power and large storage requirements. In addition, using the complete set of histogram cannot be reliable to describe the input image, because some pattern types rarely occur. The proportions of such patterns are too small to provide a reliable estimate of the occurrence possibilities of those patterns.

As such, several extensions of LBP have been proposed with an aim to increase its robustness and discriminative power. In 2002, Ojala et al. suggested an extension to LBP by considering only the so-called "uniform" patterns [12]. Uniform LBPs effectively capture the fundamental information of textures, which mainly consist of straight edges or low curvature edges [9].

In 2009, Liao et al. extended the conventional LBP approach in order to effectively capture the dominating patterns in texture images [9]. In their approach, they omitted the information related to the dominant pattern types, and only consider the information about pattern occurrence frequencies. In 2010, Guo et al. introduced a learning framework of image descriptor based on Fisher separation criteria to learn the most reliable and robust dominant pattern types considering intra-class similarity and interclass distance [4]. They applied their FSC-based learning framework with LBP and presented the FBL-LBP descriptor.

Recently in 2012, Liu et al. proposed new four descriptors to extend the conventional LBP [10], namely two local intensity-based descriptors CI-LBP and NI-LBP and two local difference-based descriptors RD-LBP and LBP-AD. However, they found that, proportions of the uniform patterns of AD-LBP are too small to provide a meaningful description of texture. Broadly speaking, even though the success of the uniform patterns with some LBP variants, the proportions of these patterns are inadequate to provide a meaningful description of texture for some other LBP variants [10].

In this paper, we propose a new-feature selection method, dominant LBP considering patten type (DLBP-CPT), capable to capture, effectively, the most reliable and robust dominant pattern types in face images. In contrast to previous Dominant LBP approaches, we take into account the dominant pattern types information. Experimental results show that pattern type represents essential information that should be included in facial image representation. The proposed approach showed better performance comparing to other dominant approaches.

This paper is organized as follows: Section 2 shows an overview of both LBP and AD-LBP. The proposed approach is described in section 3. Experiments and results are provided in section 4. Finally, discussion and conclusion are given in section 5.

## 2 The Local Binary Pattern (LBP)

### 2.1 A Brief Overview of LBP

The original LBP operator, proposed by Ojala [11], is a powerful method for texture description due to its invariance to global intensity variations. It labels the pixels of an image by thresholding a $3 \times 3$ square neighborhood with the value of the center pixel and considering the result as a binary number. Later the operator was extended to use circular symmetric neighborhoods [12], that allowed considering any radius and number of pixels in the neighborhood, see Fig. 1. Given a central pixel $x_c$ and its $p$ neighbors $x_n$, the decimal form of the resulting LBP code can be expressed as:

$$LBP_{p,r} = \sum_{n=0}^{p-1} s\left(x_n - x_c\right) 2^n, \quad s\left(x\right) = \begin{cases} 0\ , x < 0 \\ 1\ , x \geq 0 \end{cases} \tag{1}$$

Later, Ojala et al. extended the original LBP operator to use the so-called uniform patterns [12]. The number of bitwise transitions, when the binary string is circular, gives a uniformity measure $U$ of the pattern as follows:

$$U\left(LBP_{p,r}\right) = \sum_{n=0}^{p-1} \left| s\left(x_{r,n} - x_{0,0}\right) - s\left(x_{r,mod(n+1,p)} - x_{0,0}\right) \right| \tag{2}$$

The LBP operator is called uniform if its uniformity measure is at most 2. The notation $LBP_{p,r}^{u2}$ is used for the operator where the superscript $u2$ denotes the uniform patterns which have $U$ values at most 2. Uniform LBP mapping gives a separate output label for each uniform pattern and all the non-uniform patterns are assigned to a single label. The uniform mapping results in $p(p-1)+3$ different output labels, leading to a much shorter histogram representation.

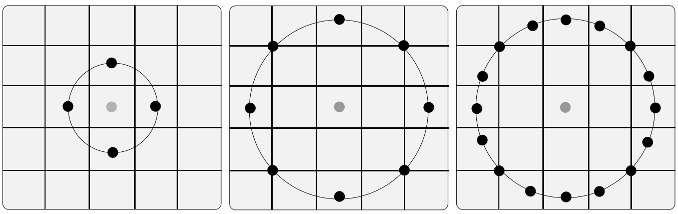

**Fig. 1.** The circular (4,1), (8,2) and (16,2) neighborhoods

### 2.2 The Angular Difference LBP (AD-LBP)

The AD-LBP descriptor uses the angular difference instead of intensity differences between the specified pixel and its neighbors, in order to have higher stability in flat image regions. Given the gray values of pairs of pixels $x_{r,n}$ and $x_{r,mod(n+\delta,p)}$, with a certain angular displacement $\delta(\frac{2\pi}{p})$, the angular difference is defined as $\Delta^{Ang}_{\delta,n} = x_{r,n} - x_{r,mod(n+\delta,p)}$, where $\delta$ is an integer such that $1 \le \delta \le \frac{p}{2}$. Therefore, the AD-LBP is computed as follows, see Fig. 2:

$$AD - LBP_{p,r} = \sum_{n=0}^{p-1} s\left(\Delta^{Ang}_{\delta,n}\right) 2^n, \quad s(x) = \begin{cases} 0, & x < \varepsilon \\ 1, & x \ge \varepsilon \end{cases} \tag{3}$$

In order to increase the operator's robustness in flat areas, the differences are thresholded at a non-zero threshold value $\varepsilon$ , that is 1% of the pixel value range. For the experiments of this paper, we set $\varepsilon = 0.01$.

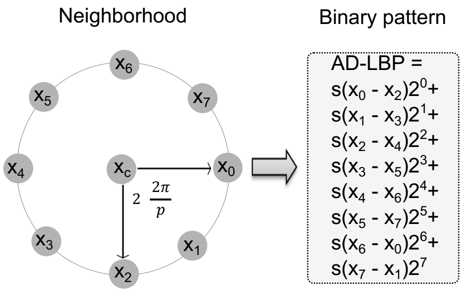


**Fig. 2.** Description of the AD-LBP operator with $\delta = 2$

## 3 Dominant LBP Considering Pattern Type (LBP)

### 3.1 Related Works and Motivation

Although the LBP approach is attractive for its invariance against monotonic gray level changes and its computational simplicity, the original LBP comes with disadvantages and limitations. For example, the LBP operator produces long histograms, and it can become intractable to estimate histograms due to the overwhelming dimensionality of it with large $p$. Also, it is demonstrated that LBP is very sensitive to noise [10].

Using uniform LBP patterns, instead of all the possible patterns has produced better recognition results in many applications. On one hand, there are indications that uniform patterns are less prone to noise, and on the other hand, the uniform mapping makes the number of possible LBP labels considerably lower and reliable estimation of their distribution requires fewer samples. Additionally, uniform LBPs detect local primitives such as spots, flat areas, edges and edge ends, which represent the majority among all LBP types [12].

However, in practice, there are some textures images have more complicated shapes and edge types. Then the uniform LBPs are not necessary to occupy the major type proportions. Also, uniform patterns will have a much smaller proportion among all LBP types, as the radius and the number of neighbors increase. Therefore, textural information cannot be effectively captured using only the uniform LBPs [4,9].

Liao et al. [9] extended the conventional LBP approach to the dominant LBP (DLBP)which make use of the most frequently occurred patterns of LBP to improve the recognition accuracy compared to the original uniform patterns.The DLBP approach considers only the pattern occurrence frequencies, regardless the information related to the dominant pattern type.

Next, Guo et al. introduced a learning framework for image descriptor design, overcomes the drawbacks of uniform LBP [4]. Considering the intra-class similarity and inter- class distance, the most reliable and robust dominant pattern types are learnt based on the Fisher separation criterion (FSC).Thus, image structures are described by the FSC-based learning (FBL) encoding method. In their experiments, FBL-LBP outperformed many other methods, including DLBP [9].

However, in some situations (e.g., large illumination variations), samples of the same class in the database may have high intra-class variations. Accordingly, the aforementioned methods suffer in terms of reliability and robustness. In case of FBL-LBP, global dominant pattern sets are constructed for each dominant region independently. For some regions the Fisher separation criterion is too hard to be applicable, as features vary greatly among samples for those regions. Thus there are no common features to be considered in the intra class similarity space, which represent those regions for some classes. In other words, some classes are not represented in the extra class similarity space. Therefore, the optimum discrimination among data cannot be guaranteed. On the other hand, neglecting the dominant pattern type, in case of DLBP [9], could probably weaken the discriminative ability under hard illumination conditions.

This motivated us to present our dominant approach for LBP considering the pattern type. The proposed approach proceeds as follows: Divide each image from the training set into m overlapping regions, and determine the most reliable dominant types for each region. Then, all the learned dominant types of each region are merged and form the global dominant types for the whole database. In this paper, we chose to apply the proposed approach on LBP and AD-LBP. The proposed approach includes two phases; learning phase and feature extraction phase as given in the following subsections.

### 3.2 The Learning Phase

Given a training image set of different classes, divide each image of the training set into m regions. To learn the most reliable and robust dominant pattern types for each region, initialize a record vector of $2^p$ entries to 0. For each region, compute the occurrence frequencies of all patterns, and then sort them in descending order. The first k most frequently occurring pattern types are sought, for each region, and the corresponding elements of the record vector are increased by 1. After all, sort the record vector of each region, and then the first k elements of each record vector are connected to be the overall dominant types for the whole database. The learning phase is described in (**Algorithm 1**).

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**Algorithm 1.** Determininghe Dominant Pattern Types

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***Input***: *$I$: a training image set, $m$: number of regions, $k$: dominant number per regions, $p$: number of neighbor pixels, and $r$: radius*
***Output***: *$Dom_set$: The dominant pattern types set*

1. **Initialize** a reference pattern type record vector $domV_j[i] = i, \quad i = 0, ..., 2^p - 1, \quad j = 1, ..., m.$
2. **Initialize** pattern histogram $domH_j[0...(2^p - 1)] = 0, \quad j = 1, ...m$
3. **FOR** each image $I$ in the training image set
   (a) **Divide** the image into $m$ overlapping regions
   (b) **FOR** $j = 0$ to $m - 1$
      i. **Initialize** the pattern histogram $H[0...(2^p - 1] = 0$
      ii. *Initialize* a reference pattern type record vector $V$ where $V[i] = i, \quad i = 0, ..., 2^p - 1$
      iii. **FOR** each center pixel $t_c \in I$
         A. **Compute** the pattern label of $t_c, l$
         B. **Increase** the corresponding bin by 1, $H[l] + +$
         END FOR
      iv. **Sort** the histogram $H$ in a descending order, Change the configuration of $V$ according to the element switching order of $H$. Now the top $h$ entries of $H$ denote the occurrence frequencies of the top $h$ most dominant patterns.
      v. **FOR** $i = 0$ to $k - 1$
         A. $domH_j[V[i]] + +$
         **END FOR**
      **END FOR**
   **END FOR**
4. **FOR** $j = 0$ to $m - 1$
   (a) **Sort** the histogram $domH_j$ in descending order. Change the configuration of $doV_j$ according to the element switching order of $domH_j$ $dom\_set_j = \{domV_j[0], ..., domV_j[k - 1]\}$
5. **Return** $Dom\_set = \{dom\_set_0, ..., dom\_set_{m-1}\}$

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### 3.3 Feature Extracting Phase

For a training, or testing, image and given the global dominant pattern types set obtained in the learning phase, extract occurrence histogram of pattern types of the features of this image. The feature vector for each image will not only encode the occurrence frequency of each dominant pattern type as in DLBP method [9], but also consider the pattern type information, which is the complementary discriminative information. This makes the proposed feature vectors more powerful in classification. The feature extraction phase is described in (**Algorithm 2**).

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**Algorithm 2.** Extracting the feature vector

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***Input***: *I: a training image set, m: number of regions, k: dominant number per regions, Dom_set: the dominant LBP set obtained by Algorithm 1, p: number of neighbor pixels, and r: radius*
***Output***: *The feature vector corresponding to image I*

1. **FOR** $j = 0$ to $m - 1$
   (a) **Initialize** the pattern histogram, $H[0...(2^p - 1] = 0$
   (b) **FOR** each center pixel $t_c \in I$
      i. **Compute** the pattern label of $t_c, l$
      ii. **Increase** the corresponding bin by 1, $H[l]++$
      END **FOR**
   END **FOR**
2. **Return** $H[Dom\_set_0[0], ..., Dom\_set0[k-1]...Dom\_setm-1[0], ..., Dom\_set_{m-1}[k-1]]$ as the feature vector

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# 4 Experiments and Results

## 4.1 Experiments Setting

We demonstrate the performance of the proposed approach in face identification 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.The testing images are divided into 5 subsets; each includes 6 illumination conditions, according to severity of illumination conditions from moderate to extreme luminance. Fig. 3 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.

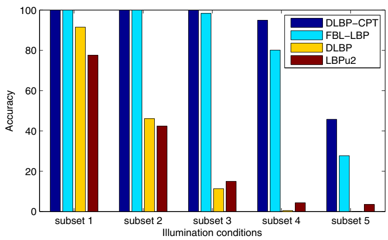
Images are manually cropped and resized into $48 \times 48$ pixels. We set $r = 1$ and $p = 8$, and divide each image into $3 \times 3$ overlapping regions. The dominant type set is determined for each database by applying **Algorithm 1** on both the LBP and AD-LBP operators. Then, a feature vector for each test image is extracted using **Algorithm 2**. The support vector machine (SVM) is used as a 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. 3.** Samples of the extended Yale B face database from moderate up to sever illumination

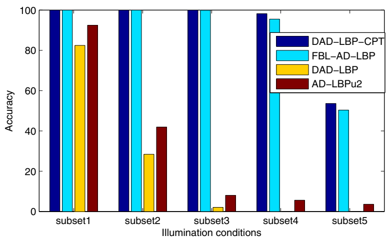
## 4.2 Experimental Results

We proceed now to the evaluation phase of the proposed approach. Toward a fair evaluation, we conduct a comparison among the proposed approach, the traditional uniform approach [12], and the other dominant approaches [9] and [4] in face identification. Fig. 4(a) shows the comparison among the four approaches with the LBP descriptor, whereas Fig.4(b) shows the comparison among the four approaches with the ADLBP descriptor using the Extended Yale B database.

As a first observation, the performance of the proposed approach with AD-LBP descriptor is better than that with LBP descriptor. Thus, applying our approach with AD-LBP instead of using uniform patterns has improved its performance given originally in [10]. Also, it is clear that the proposed approach outperforms the other three approaches either with the LBP descriptor or the AD-LBP descriptor. In addition, we can observe that the performance of both the uniform pattern approaches ($LBP^{u2}$ and $AD-LBP^{u2}$) and the other dominant approach (DLBP and DAD-LBP) is degraded with illumination, especially, with severe illumination conditions (subset 2 - subset 5).




(a)




(b)

**Fig. 4.** Face identification rates for(a) LBP (b) AD-LBP descriptors

**Table 1.** Face identification rates for LBP operator using the CMU-PIE

| $(p, r)$ | $DLBP-CPT$ | $FBL-LBP$ | $DLBP$ | $LBP^{u2}$ |
|---|---|---|---|---|
| (8,1) | 93.24% | 76.36% | 32.64% | 45.74% |
| (8,2) | 94.35% | 65.91% | 51.63% | 45.49% |

**Table 2.** Face identification rates for AD-LBP operator using the CMU-PIE

| $(p, r)$ | $DAD-LBP-CPT$ | $FBL-AD-LBP$ | $DAD-LBP$ | $AD-LBP^{u2}$ |
|---|---|---|---|---|
| (8,1) | 96.52% | 82.89% | 19.67% | 16.14% |
| (8,2) | 96.35% | 78.19% | 20.87% | 28.24% |

In contrast, the proposed approach and the FBL approach (FBL-LBP and FBL-ADLBP) show a similar performance in case of moderate illumination conditions (subset 1- subset 2), whereas their performance starts to degrade gradually with severe illumination (subset 3 subset 5) with clear superiority for our approach over the FBL approach in these hard luminance conditions.

The expremintal results using the CMU-PIE database, again demonstrate the superiority of the proposed approach over the other approaches with both the LBP (see Table 1) and AD-LBP (see Table 2) operators.

## 5 Discussion and Conclusion

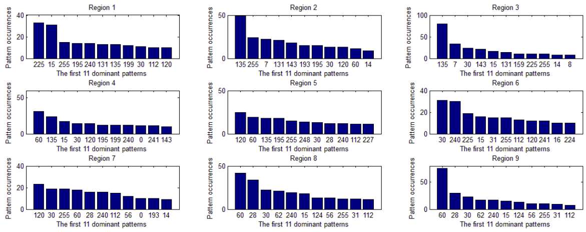
In the overall comparison with DLBP, FBL-LBP and uniform LBP, the proposed DLBP-CPT descriptor provides better performance in face identification task. It is clear that the pattern type has an important role in the discrimination process. For example, the DLBP [9] approach takes into account only the pattern occurrence information, and neglects the pattern type information. This affects the discriminative power and robustness of DLBP against hard illumination conditions.

To assure this conclusion, Fig. 5 shows two samples of two different subjects, where we divide each sample into $3 \times 3$ overlapping regions. The pattern occurrences of, for example, the first 11 DLBP patterns are computed per region per image. As it is illustrated in Fig. 6(a) and Fig. 6(b) for DLBP, the histograms of the pattern occurrences, for the two subjects, are very similar to each other. In other words, it becomes difficult to distinguish or classify these two subjects using only the information of the pattern occurrences. However, the corresponding dominant pattern types (x-axis in Fig. 6) for the two images are obviously different from each other. This means that, considering the pattern types, certainly, will enhance the classification task. Indeed, considering the pattern types gives our approach extra discriminative ability as it is illustrated in Fig. 7(a) and Fig 7(b).

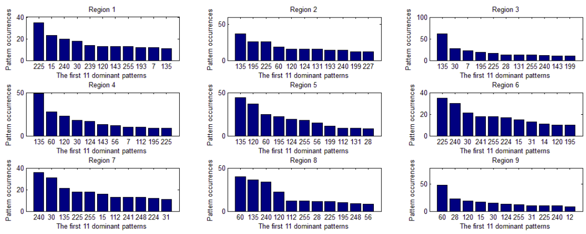
On the other hand, however the FBL-LBP descriptor considers the dominant pattern type as complementary discriminative information, which gives it

(a) (b)

**Fig. 5.** Two faces of two different subjects

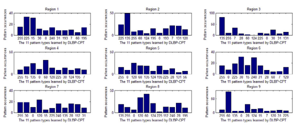


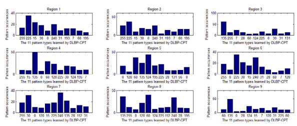

(a)




(b)

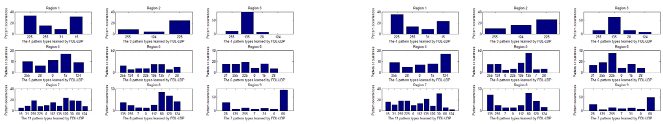
**Fig. 6.** The pattern occurrences of the first 11 dominant patterns of each region produced by DLBP (a) for Fig. 5(a) and (b) for Fig. 5(b)





(a) (b)

**Fig. 7.** The dominant pattern occurrences of each region produced by DLBP-CPT (a) for Fig. 5(a) and (b) for Fig. 5(b)



(a) (b)

**Fig. 8.** The dominant pattern occurrences of each region produced by FBL-LBP (a) for Fig. 5(a) and (b) for Fig. 5(b)

superiority over the DLBP, the Fisher separation criterion may decrease its discriminative ability. As it is illustrated in Fig. 8, for some regions, the Fisher separation criterion yields inadequate extra class similarity space that does not represent all classes, even though in this paper we increased the threshold into 95% instead of 90% described by authors in [4]. In other words, this small number of selected features is inadequate to provide a meaningful description for this number of classes. Therefore, the optimum discrimination status among the input data cannot be guaranteed. In contrast, the FBL-AD-LBP descriptor produces long histograms (215 bins), as the AD-LBP operator demonstrates robustness against illumination variations. Moreover, as the number of classes increases in case of the CMU-PIE database, more dominant pattern types are selected, producing long histograms as well (more than 300 bins for FBL-LBP). On the contrary, the histogram size of the proposed approach is independent of the number of classes and is less sensitive to the illumination variations.

In conclusion, this paper introduced a novel feature selection method DLBP-CPT, capable to extract the most reliable and robust dominant patterns in face image. In contrast to the DLBP approach, the proposed approach takes into account the dominant pattern types information. We found that the pattern type represents essential information that should be included, especially, in face image representation across variation of illumination. We applied the proposed approach on the conventional LBP and AD-LBP operators to evaluate its discriminative power. It is shown through the conducted experiments, using the Extended Yale B and the CMU-PIE databases, that the proposed approach is more reliable to represent the dominating pattern information in the facial images than the conventional uniform LBP and other dominant approaches. Moreover, it is shown that applying the proposed operator with the AD-LBP operator, is more adequate than using the conventional uniform pattern approach, and has increased the its performance significantly.

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