# Discriminative Local Binary Pattern for Image Feature Extraction

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**Abstract.** Local binary pattern (LBP) is widely used to extract image features in various visual recognition tasks. LBP is formulated in quite a simple form and thus enables us to extract effective image features with a low computational cost. There, however, are some limitations mainly regarding sensitivity to noise and loss of image contrast information. In this paper, we propose a novel LBP-based image feature to remedy those drawbacks without degrading the simplicity of the original LBP formulation. Encoding local pixel intensities into binary patterns can be regarded as separating them into two modes (clusters). We introduce Fisher discriminant criterion to optimize the LBP coding for exploiting binary patterns stably and discriminatively with robustness to noise. Besides, image contrast information is incorporated in a unified way by leveraging the discriminant score as a weight on the corresponding binary pattern; thereby, the prominent patterns are emphasized. In the experiments on pedestrian detection, the proposed method exhibits superior performance compared to the ordinary LBP and the other methods, especially in the case of lower-dimensional features.

**Keywords:** Visual recognition · Image feature · Local binary pattern · Discriminant criterion

## 1 Introduction

In visual recognition, it is a fundamental procedure to extract features from images, which is followed by classification. While various types of image feature have been proposed so far [3,11,21,24], local binary pattern (LBP) [15,20] is one of the commonly used features due to its simple formulation and high performance. The LBP method has been mainly applied to measure texture characteristics [6,7,15–17], and in recent years it is shown to be favorably applicable to various kinds of visual recognition tasks besides texture classification, such as face recognition [1,22], face detection [8], pedestrian detection [24] and sound classification [10].

The LBP method encodes local pixel intensities into binary patterns on the basis of the center pixel intensity in the local region. There are some limitations in LBP, mainly regarding sensitivity to noise and loss of local textual information, *i.e.*, image contrast. In the last two decades, considerable research effort has been


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made to address those drawbacks of LBP leading to variants of LBP. In [17], the image contrast information is separately extracted by computing variance of local pixel intensities and joint distribution of the contrast feature and LBP is employed. The contrast information, local variance, is also naturally incorporated into LBP formulation via weighting binary patterns in [6]. LBP can be combined with HOG features [3] to compensate such information loss [24]. The robustness to noise is improved by developing binary patterns to ternary patterns [22] which are further extended to quinary ones [14], though the number of patterns corresponding to the feature dimensionality is significantly increased. It is also possible to build noise-robust LBP by simply considering local statistics, mean [8] or median [7], as a threshold instead of the center pixel intensity in coding. To further improve robustness, we have recently extended LBP to fully incorporate statistical information, mean and variance, in the processes both of coding and weighting. For more elaborated review of LBP, refer to [20].

In this paper, we propose a novel method to extract LBP-based image features with retaining simplicity of the original LBP formulation as well as remedying the limitations of LBP. We first generalize the LBP formulation by focusing on the two fundamental processes of coding and weighting, and then along the line of [6–8,10], propose *discriminative LBP* by providing a discriminative approach to determine those two fundamentals. In the discriminative approach, LBP coding is regarded as separating local pixel intensity distribution into two modes (clusters) and from that viewpoint, a threshold is optimized by maximizing the Fisher discriminant score which is further utilized in weighting. Thereby, the discriminative LBP stably encodes the local pixel intensities into binary patterns via the optimization with high robustness to noise, also incorporating image contrast information in a unified manner. Due to simplicity as in the ordinary LBP, the proposed method can be easily integrated with the sophisticated extension which has been applied to LBP, such as uniform pattern [16] and combination with the other image features [24].

## 2 Discriminative Local Binary Pattern

In this section, we detail the proposed method, called *discriminative LBP*. We first give a general formulation for extracting local binary patterns (LBP) [15] with review of the LBP variants based on that formulation. Then, the discriminative perspective is introduced into the processes of coding and weighting which are fundamental in the general formulation.

### 2.1 General Formulation for LBP

Let $\boldsymbol{r} = (x, y)$ be a spatial position in a two-dimensional image $I$ and $I(\boldsymbol{r})$ indicates the pixel intensity at that position. In LBP [15], local pixel intensities are focused on and encoded by binarizing individual pixel intensities as follows;

$$\mathtt{code}(\mathcal{L}_{\boldsymbol{c}}; \tau_{\boldsymbol{c}}) = \sum_{j=1}^{N} 2^{j-1} [\![ I(\boldsymbol{r}_i) > \tau_{\boldsymbol{c}} ]\!] \quad \in \{0, \cdots, 2^N - 1\}, \tag{1}$$

**Table 1.** Comparison in variants of LBP

| method | $\tau$ | $w$ |
|---|---|---|
| ordinary LBP [20] | $I(\boldsymbol{c})$ | 1 |
| median LBP (MBP) [7] | $\mathtt{median}(I)$ | 1 |
| improved LBP [8] | $\mu$ | 1 |
| LBP variance [6] | $I(\boldsymbol{c})$ | $\sigma^2$ |
| statistics-based LBP [10] | $\mu$ | $\sigma$ |
| discriminative LBP (proposed) | $\arg\max \sigma_B$ | $\sqrt{\frac{\max \sigma_B^2}{\sigma^2+C}}$ |

where $[\![\cdot]\!]$ indicates the Iverson bracket that equals to 1 if the condition in the brackets is satisfied and 0 otherwise. $\mathcal{L}_{\boldsymbol{c}} = \{\boldsymbol{r}_i\}_{i=1}^N$ denotes a local pixel configuration centered at $\boldsymbol{c} \in \mathbb{R}^2$, comprising $N$ spatial positions $\boldsymbol{r}_i$ close to $\boldsymbol{c}$. For example, the simplest and widely used configuration consists of $N = 8$ surrounding pixels in a $3 \times 3$ local patch and it is further extended in a multi-scale setting [17]. Though the number of codes (binary patterns) is exponentially increased according to $N$, it is also possible to suppress the pattern variation by considering uniform patterns [16]. As shown in (1), the local image pattern on $\mathcal{L}_{\boldsymbol{c}}$ is encoded into a $N$-bit code by means of binarization of pixel intensities with a threshold $\tau_{\boldsymbol{c}}$. Finally, LBP codes computed by (1) are aggregated to LBP features $\boldsymbol{x} \in \mathbb{R}^{2^N}$ over a region of interest $\mathbb{D}$,

$$x_i = \sum_{\boldsymbol{c}\in\mathbb{D}} w_{\boldsymbol{c}} [\![\mathtt{code}(\mathcal{L}_{\boldsymbol{c}}; \tau_{\boldsymbol{c}}) = i-1]\!], \quad i \in \{1, \cdots, 2^N\}, \tag{2}$$

where $w_{\boldsymbol{c}}$ is a voting weight which indicates significance of the local binary pattern.

LBP variants can be placed in this general formulation as shown in Table 1. As to coding, an ordinary LBP [20] is established by setting $\tau = I(\boldsymbol{c})$ and in [7,8] it is modified by local statistics, $\tau = \mu = \frac{1}{N}\sum_i I(\boldsymbol{r}_i)$ and $\tau = \mathtt{median}_i[I(\boldsymbol{r}_i)]$, respectively. On the other hand, the local variance, $\sigma^2 = \frac{1}{N}\sum_i (I(\boldsymbol{r}_i) - \mu)^2$, which is separately employed as local image contrast in [17], is incorporated as the weight $w$ in [6], and very recently, we have proposed statistics-based LBP [10] by effectively applying those simple statistics to both coding and weighting as $\tau = \mu$ and $w = \sigma$; it should be noted that most methods simply employ *hard* voting weights, *i.e.*, $w = 1$. Thus, we can say that the LBP method generally contains two essential parameters $\tau$ and $w$ to be designed a priori for extracting effective image features.

### 2.2 Discriminative Coding

We propose a novel coding method which optimizes the threshold $\tau$ and the voting weight $w$ in (1, 2) based on a discriminative criterion.

The LBP coding (1) can be viewed as approximating local pixel intensity distribution in $\mathcal{L}_{\boldsymbol{c}}$ by two modes separated by the threshold $\tau$. In a least squares sense, which also means to fit Gaussian models from a probabilistic viewpoint, we can measure *quality* of the code by the following residual error,

$$\epsilon(\tau) = \frac{1}{N}\left\{\sum_{i|I(\boldsymbol{r}_i)\leq\tau}(I(\boldsymbol{r}_i)-\mu_0)^2 + \sum_{i|I(\boldsymbol{r}_i)>\tau}(I(\boldsymbol{r}_i)-\mu_1)^2\right\}, \tag{3}$$

$$\text{where}\quad \mu_0 = \frac{1}{N_0}\sum_{i|I(\boldsymbol{r}_i)\leq\tau} I(\boldsymbol{r}_i),\quad N_0 = \sum_i [\![ I(\boldsymbol{r}_i)\leq\tau ]\!], \tag{4}$$

$$\mu_1 = \frac{1}{N_1}\sum_{i|I(\boldsymbol{r}_i)>\tau} I(\boldsymbol{r}_i),\quad N_1 = \sum_i [\![ I(\boldsymbol{r}_i)>\tau ]\!]. \tag{5}$$

Here, we represent two modes with the mean $\mu_0$ and $\mu_1$, respectively. The residual error $\epsilon$ corresponds to within-class variance $\sigma_W^2$ for the classes which are partitioned by the threshold $\tau$. Minimizing $\epsilon$ coincides with maximization of Fisher discriminant score [4], actually maximization of between-class variance $\sigma_B^2$;

$$\sigma_B^2(\tau) = \frac{N_0}{N}(\mu_0-\mu)^2 + \frac{N_1}{N}(\mu_1-\mu)^2 = \frac{N_0 N_1}{N^2}(\mu_1-\mu_0)^2. \tag{6}$$

Thus, the threshold $\tau$ is optimized by

$$\gamma^* = \arg\max_{\tau\in\{I(\boldsymbol{r}_i)\}_{i=1}^N} \sigma_B^2(\tau). \tag{7}$$

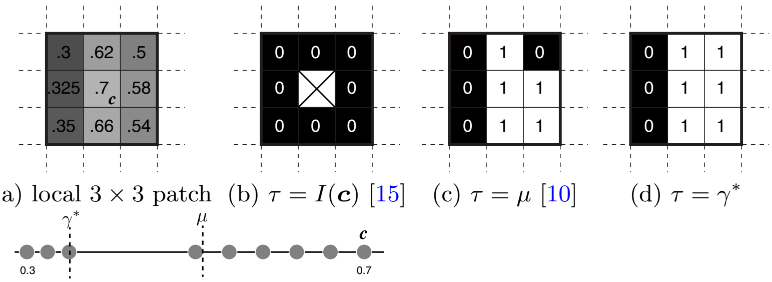
Thereby, the proposed discriminative coding with $\gamma^*$ reduces the error ($\epsilon$) in assigning binary codes (1) as well as enhances the discriminativity ($\sigma_B$) between two modes partitioned by $\gamma^*$. This procedure is performed in the same way as Otsu's auto-thresholding method [18] applied to pixel intensities $\{I(\boldsymbol{r}_i)\}_{i=1}^N$.

Next, we can accordingly determine the voting weight $w$ as the (square root of) discriminant score;

$$w = \sqrt{\frac{\sigma_B^2(\gamma^*)}{\sigma^2 + C}}, \tag{8}$$

where $C$ is a small constant to avoid numerical instability for smaller $\sigma$, especially in the case that local pixel intensities are close to uniform; in this study, we set $C = 0.01^2$ for pixel intensity scale $[0, 1]$. This weight reflects how far the two modes are separated by $\gamma^*$ and therefore is considered to measure significance of the corresponding binary pattern.

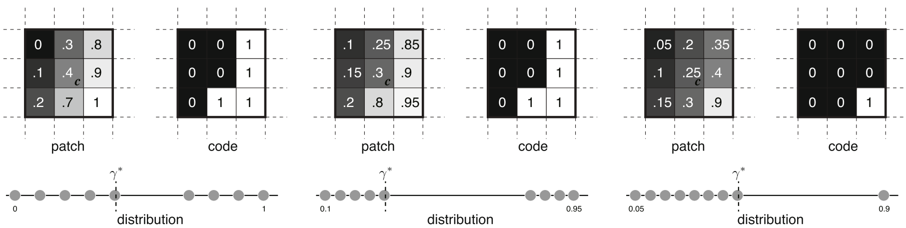
The proposed coding is built on the optimization (7), while the other methods employ hard coding [7,8,15] and soft coding with simple statistics [6,10]. The computational cost for the optimization is negligible due to a small number of pixels $N$ to be focused on in $\mathcal{L}_{\boldsymbol{c}}$; a brute-force approach optimizes (7) with computational complexity $O(N^2)$, but $N$ is empirically quite small, *e.g.*, $N = 8$ or 9 in most cases.




(a) local $3 \times 3$ patch (b) $\tau = I(\boldsymbol{c})$ [15] (c) $\tau = \mu$ [10] (d) $\tau = \gamma^*$

(a') pixel intensity distribution

**Fig. 1.** Examples of LBP codes by various thresholds. A local patch (a) of pixel intensity distribution (a') is encoded into binary codes by ordinary LBP $\tau = I(\boldsymbol{c})$ [15] (b), statistics-based LBP $\tau = \mu$ [10] (c) and the proposed method $\tau = \gamma^*$ (d). In (c, d), $\mathcal{L}_{\boldsymbol{c}}$ includes the center pixel $\boldsymbol{c}$. The proposed method produces a stable code with a large margin which is hardly affected by noise.




(a) $w = 0.92$ (b) $w = 0.98$ (c) $w = 0.89$

**Fig. 2.** Examples of weights in the proposed method. In each figure, the input local patch, its pixel intensity distribution and the resultant binary pattern (code) are shown in top-left, bottom and top-right, respectively. Details are in the text.

### 2.3 Characteristics of Discriminative Coding

The ordinary LBP [15] of $\tau = I(\boldsymbol{c})$ and $w = 1$ always assigns a local image pattern with one of the LBP codes, no matter how the image pattern is less significant, such as being close to uniform. The LBP coding takes into account only magnitude relationships between the pixel intensities of neighborhoods and that of a center pixel, $I(\boldsymbol{c})$, in disregard of the margin. Thus, even a small fluctuation on the pixels whose intensities are close to $I(\boldsymbol{c})$ easily degenerates the LBP code by breaking up the magnitude relationships, which results in totally different features. In other words, the binary codes on the pixel intensities of a small margin from $I(\boldsymbol{c})$ are vulnerable to noise, causing unstable LBP features.

On the other hand, the proposed coding (Section 2.2) extracts a discriminative structure of a local pixel intensity distribution, exhibiting high robustness to noise. In the structure, two modes endowed by the threshold $\gamma^*$ are discriminatively separated with a statistically large margin due to maximizing Fisher discriminant score in (7), which exhibits stable patterns as shown in Figure 1.

Besides, for weighting, the significance of the local pattern is effectively measured by Fisher discriminant score (8) as shown in Figure 2. Even for the similar image patches resulting in the same code, the patch of sharply separated pixel intensities gets the larger weight than that of blurred intensities (Figure 2ab). On the other hand, smaller weight is assigned to the patch of which distribution is highly biased (Figure 2c), even though it is sharply separated. Such a biased distribution can be regarded as a noisy pattern containing a outlier and thus it is favorable that such code contributes less to the feature.

It should be noted that the proposed LBP is invariant to affine transformation of pixel intensities, $aI(\boldsymbol{r})+b$, in terms of coding and weighting as in the ordinary LBP, while the statistics-based LBP [10] is affected by scaling $a$ in the weight $w=\sigma$.

The proposed method effectively extracts the geometrical characteristics in an image, various patterns of gradients and curvatures which are considered to be fundamental local geometries for describing an image structure. Those essential characteristics are represented by the local binary patterns which reflect discriminative structures of the pixel intensity distributions with high robustness to noise. Through weighting by Fisher discriminant scores, the patches of less texture are ignored, contributing less to the feature, while distinctive ones, such as around object edges, are highly focused on by large weights.

## 3 Techniques for Image Feature

We mention some practically useful techniques for extracting effective image features [24].

**Normalization.** The discriminative LBP produces features in a histogram form which is regarded as a discrete probability distribution over the LBP codes. The Hellinger (Bhattacharya) kernel can be effectively applied to measure the similarity between those probability distributions [2], and it is possible to embed the kernel in a (linear) dot product of the feature vectors by normalizing the features in the following form [19]; $\hat{\boldsymbol{x}} = \sqrt{\frac{\boldsymbol{x}}{\|\boldsymbol{x}\|_1}}$. This normalization enhances the discriminative power of features by enhancing difference on smaller feature values while suppressing it on larger values via the square root function.

**Cell-Structured Feature.** In the case of object classification, it is demanded to extract features related to *parts* which compose the target objects. Those part-based features are naively extracted by partitioning the object image into subregions, called *cells*, on which the features are computed [3,11]. The final feature is built by simply concatenating all cell-wise features. Note that in this study, the above-mentioned normalization is applied to respective cell-wise feature vectors before concatenation.

**Binary Pattern Reduction.** The dimensionality of the LBP-based feature is exponentially increased according to the number of pixels $N$ in the local patch $\mathcal{L}_{\boldsymbol{c}}$. If one wants to reduce the feature dimensionality such as due to memory limitation, binary patterns can be reduced by considering *uniform patterns* [16]. Uniform patterns are constructed by allowing only a few times 0/1 transitions on the neighborhood pixels surrounding the center $\boldsymbol{c}$; 256-dimensional features of $N = 8$ are reduced to 58-dimensional ones by uniform patterns allowing only two times 0/1 transitions and 512-dimensional features of $N = 9$ including the center become 114-dimensional ones as well[1].

## 4 Experimental Results

We apply the proposed method to pedestrian detection tasks using the Daimler Chrysler pedestrian benchmark dataset [13] for evaluating the performance from various aspects and INRIA person dataset [3].

In feature extraction, the local patch $\mathcal{L}_{\boldsymbol{c}}$ is restricted within $3 \times 3$ pixels since the larger patch degrades performance as reported in [24], and we apply $L_2$-Hellinger normalization to LBP-based feature vectors.

### 4.1 Performance Analysis on Daimler Chrysler Dataset

The Daimler Chrysler pedestrian dataset is composed of five disjoint sets, three for training and two for test. Each set has 4,800 pedestrian and 5,000 pedestrian-free images of $18 \times 36$ pixels. For constructing cell-structured features, we consider cells of $6 \times 6$ pixels, producing $3 \times 6$ cells over an image. We follow the standard evaluation protocol on this dataset, in which the linear classifier is trained on two out of three training sets by using liblinear [5] and is tested on each of the test sets, producing six evaluation results. We measure the average of accuracies at equal error rate across the six results.

In the following, we analyze in detail the proposed method in terms of coding by $\tau$, weighting with $w$ and feature dimensionality controlled by a local patch $\mathcal{L}_{\boldsymbol{c}}$ and pattern reduction (Section 3). Performance results in various settings are shown in Table 2.

**Coding and Weighting.** Compared to the ordinary LBP (the first row in Table 2), the proposed method (the last row) significantly improves the performance with and without uniform patterns (Table 2ab). Under the condition of the same feature dimensionality, the method is still largely superior to ordinary LBP as shown in lines 1 and 5 of Table 2, though only weighting and coding are modified to discriminative ones (Section 2.2). In addition, our method outperforms the statistics-based LBP [10] in all feature dimensionalities; see lines 3, 5, 7 and 9 in Table 2. We further set the weighting as $w = 1$ in both statistics-based

[1] 58 patterns for $N = 8$ consist of 1 flat pattern for zero 0/1 transition, 56 moderate patterns for less than or equal to twice transitions and 1 messy pattern for greater than twice transitions. In $N = 9$, we consider 1 flat and 1 messy patterns no matter what the center pixel is, and $112 = 56 \times 2$ moderate patterns according to the center pixel state.

**Table 2.** Performance analysis on Daimler Chrysler dataset for various settings in LBP formulation. The local patch $\mathcal{L}_{\boldsymbol{c}}$ of $N = 8$ excludes the center pixel. The number of dimensionality of cell-wise features is shown in the column of 'Dim.'. The performances of the proposed method are underlined.

| | (a) Full binary pattern | | | | | (b) Uniform pattern | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\mathcal{L}_{\boldsymbol{c}}$ | $\tau$ | $w$ | Dim. | Acc. (%) | $\mathcal{L}_{\boldsymbol{c}}$ | $\tau$ | $w$ | Dim. | Acc. (%) |
| 1. | $N=8$ | $I(\boldsymbol{c})$ | 1 | 256 | 92.29 | $N=8$ | $I(\boldsymbol{c})$ | 1 | 58 | 91.32 |
| 2. | $N=8$ | $\mu$ | 1 | 256 | 94.04 | $N=8$ | $\mu$ | 1 | 58 | 93.42 |
| 3. | $N=8$ | $\mu$ | $\sigma$ | 256 | 94.32 | $N=8$ | $\mu$ | $\sigma$ | 58 | 93.64 |
| 4. | $N=8$ | $\gamma^*$ | 1 | 256 | 95.02 | $N=8$ | $\gamma^*$ | 1 | 58 | 94.71 |
| 5. | $N=8$ | $\gamma^*$ | $\sqrt{\frac{\sigma_B^2}{\sigma^2+C}}$ | 256 | $\underline{95.11}$ | $N=8$ | $\gamma^*$ | $\sqrt{\frac{\sigma_B^2}{\sigma^2+C}}$ | 58 | $\underline{94.77}$ |
| 6. | $N=9$ | $\mu$ | 1 | 512 | 94.62 | $N=9$ | $\mu$ | 1 | 114 | 94.23 |
| 7. | $N=9$ | $\mu$ | $\sigma$ | 512 | 94.87 | $N=9$ | $\mu$ | $\sigma$ | 114 | 94.40 |
| 8. | $N=9$ | $\gamma^*$ | 1 | 512 | 95.12 | $N=9$ | $\gamma^*$ | 1 | 114 | 94.93 |
| 9. | $N=9$ | $\gamma^*$ | $\sqrt{\frac{\sigma_B^2}{\sigma^2+C}}$ | 512 | $\underline{95.25}$ | $N=9$ | $\gamma^*$ | $\sqrt{\frac{\sigma_B^2}{\sigma^2+C}}$ | 114 | $\underline{95.16}$ |

LBP and our method in order to give light on the effectiveness of the discriminative coding with threshold $\gamma^*$. A threshold in coding is crucial to encode the local pixel intensities into a binary pattern, while weighting works just for assigning significance to those patterns. Comparing the methods of $w = 1$, thresholds $\mu$ and $\gamma^*$ are superior to the ordinary threshold $I(\boldsymbol{c})$ and in particular, our discriminative threshold $\gamma^*$ significantly outperforms both of $\mu$ and $I(\boldsymbol{c})$. Thus, it is confirmed that the proposed method which discriminatively optimizes the threshold can effectively work in constructing local binary patterns for image features. By incorporating discriminative weights, the performance is further improved as shown in lines 4-5 and 8-9.

**Dimensionality.** By controlling a local patch $\mathcal{L}_{\boldsymbol{c}}$ and applying the uniform pattern (Section 3), the feature dimensionality is halved, accordingly causing a little performance degeneration; compare (a) with (b), and lines 2-5 with 6-9 in Table 2. Note that in the case that a local patch $\mathcal{L}_{\boldsymbol{c}}$ is of $N = 8$, the proposed and statistics-based methods do not take into account the center pixel intensity $I(\boldsymbol{c})$ at all in coding and weighting. Figure 3 graphically summarizes the performance results from the viewpoint of the feature dimensionalities. The performance gain achieved by the proposed method is larger in the lower dimensional features. This is because the discriminative power per feature element (binary pattern) is higher in the proposed method due to the discriminative coding and thus even lower dimensional features work well in classification. Thus, we can say that the proposed method is effective especially for lower dimensional LBP features

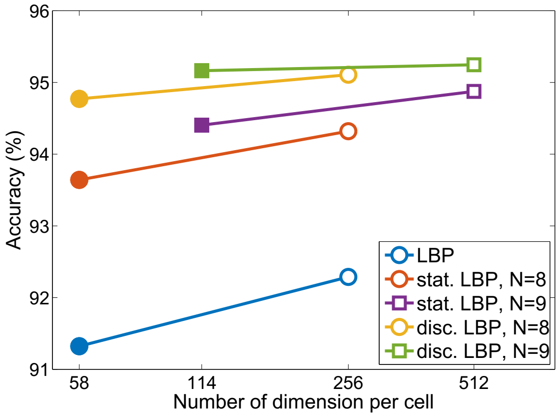



**Fig. 3.** Performance analysis on the Daimler Chrysler dataset in terms of feature dimensionality. Empty and filled markers indicate the performances of full binary patterns and uniform patterns, respectively. The horizontal axis shows dimensionality in log scale. This figure is best viewed in color.

**Table 3.** Performance comparison to the other methods.

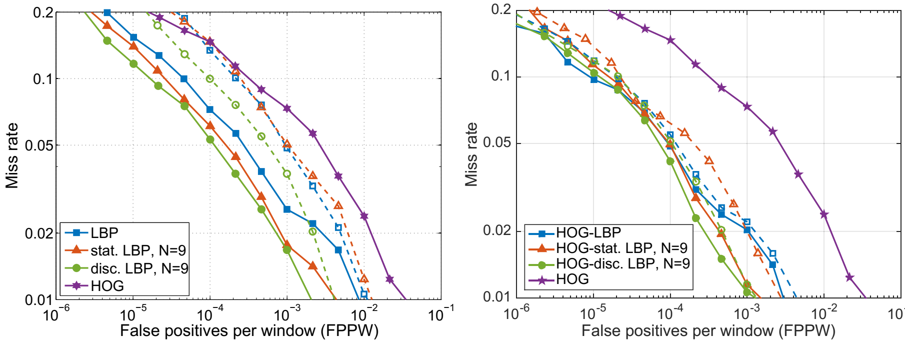
| Method | Ours, $N=9$, full | Ours, $N=9$, uniform | HOG [3] | [12] | [23] | [9] |
|---|---|---|---|---|---|---|
| Acc. (%) | **95.25** | **95.16** | 86.41 | 89.25 | 91.10 | 94.32 |

such as by applying the uniform pattern, which is practically useful by saving memory usage for features. Based on the trade-off between performance and dimensionality, we recommend to apply the proposed method with the uniform pattern and $N = 9$ local patch including the center pixel.

**Comparison to the Other Methods.** The proposed method is compared to the other methods than LBP; HOG [3], additive kernel based feature maps [12, 23] and higher-order co-occurrence [9]. Although our method is quite simple, the performance is superior to those methods; note that even the method of $N = 9$ with the uniform pattern outperforms those state-of-the-arts.

### 4.2 INRIA Person Dataset

Next, the proposed method is tested on the INRIA person dataset [3]. It contains 2,416 person annotations and 1,218 person-free images for training, and 1,132 person annotations and 453 person-free images for test; the person annotations (bounding boxes) are scaled into a fixed size of $64 \times 128$ pixels. Cell-structured features are computed on cells of $8 \times 8$ or $16 \times 16$ pixels, producing $8 \times 16$ or $4 \times 8$ cells on a detection window of $64 \times 128$ pixels. In each cell, LBP-based features with *uniform patterns* of $N = 9$ are extracted to reduce the feature dimensionality. The performance is shown in Figure 4 where for quantifying and




(a) single feature (b) combined feature

**Fig. 4.** Performance comparison on the INRIA dataset. The solid lines show the performance of LBP-based features with cells of $8 \times 8$ pixels while the dashed lines are for cells of $16 \times 16$ pixels. Note that the uniform patterns are applied to LBP-based features. The performance of single type of feature is shown in (a), while that of combined features with HOG is in (b). The ordinary HOG-LBP method [24] is denoted by HOG-LBP.

comparing methods, we plotted detection error trade-off curves by calculating miss rate and false positive rate per detection window.

As shown in Figure 4a, the proposed method outperforms LBP-related methods [10,15] and HOG [3] in both cases of $8 \times 8$ and $16 \times 16$ px cells. Note that the method with cells of $16 \times 16$ pixels produces 3648-dimensional feature vector which is close to HOG dimensionality (3780 dimension). The larger cell of $16 \times 16$ pixels contains a substantial number of pixels, *i.e.*, LBP codes, to construct features, which statistically contributes to increase robustness of noise-sensitive LBP features; the LBP method becomes even comparable to the statistics-based LBP method [10] as shown in Figure 4a (comparing dashed lines for $16 \times 16$ px cells with solid ones for $8 \times 8$ px cells). In contrast, the proposed method is superior to the LBP method in any cases due to discriminative coding.

Finally, the LBP-based features are combined with HOG as proposed in [24]; Figure 4b shows the performance results. The performance is improved by the combination and the proposed method again outperforms the ordinary HOG-LBP [24].

## 5 Conclusion

In this paper, we have proposed a novel LBP-based method to extract effective image features. We generalize the LBP formulation by focusing on the two fundamental processes of coding and weighting, and the proposed method provides a discriminative approach to determine those two fundamentals. In the discriminative approach, LBP coding which actually binarizes pixel intensities by a threshold is regarded as separating a local pixel intensity distribution into two modes, and from that viewpoint the threshold is optimized by maximizing the Fisher discriminant score which is subsequently employed in weighting. The experimental results on pedestrian detection show that the proposed method exhibits favorable performance compared to the other methods, and in particular, the method works well for lower-dimensional features.

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