Extended Set of Local Binary Patterns for Rapid Object Detection

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Abstract *The paper presents two new encoding schemes for representation of the intensity function in a local neighborhood. The encoding produces binary codes, which are complementary to the standard local binary patterns (LBPs). Both new schemes preserve an important property of the LBP, the invariance to monotonic transformations of the intensity. Moreover, one of the schemes possesses invariance to gray scale inversion. The utility of the new encodings is demonstrated in the framework of AdaBoost learning.*

The new LBP encoding schemes were tested on the face detection, car detection and gender recognition problems using the CMU-MIT frontal face dataset, the UIUC Car dataset and the FERET dataset respectively.

Experimental results show that the proposed encoding methods improve both the accuracy and the speed of the final classifier. In all tested tasks, a combination of the encoding schemes outperforms the original one. No LBP encoding scheme dominates, the relative importance of the schemes is problem-specific.

1 Introduction

Object detectors based on boosted combinations of efficiently computable features such as Haar wavelets or Local binary patterns (LBP) represent the state-of-the-art for a wide range of detection problem. In particular, detectors exploiting LBPs have achieved highly competitive results in areas including texture and dynamic texture classification [14, 15, 28, 29], face detection [4, 7, 26, 23], face recognition [2, 27, 25, 11], gender classification [20] and facial expression recognition [29, 30].

The LBP is a simple local descriptor which generates a binary code for a pixel neighbourhood. Despite its simplicity, a number of LBP modifications and extensions have been proposed. Most of the changes focus either on the definition of the location where gray value measurement are taken or on post-processing steps that improve discriminability of the binary code.

In this work, the power of LBP features is enhanced by introducing two new schemes for generating binary codes, also referred to as "rules". The new rules are compatible with the original methodology, i.e. the same number of bits is generated. The new rules preserve an important property of the

original LBP, the invariance to monotonic transformations of the intensity functions. As a novelty, one of the rules also possesses invariance to gray scale inversion. The new rules are intended to supplement and complement, not substitute, the original LBP coding scheme.

We experimentally show that, in conjunction with the algorithms for feature selection like AdaBoost and WaldBoost, the combination of different encoding rules improves accuracy and speed of the final classifier when compared with a classifier based on a single rule.

The new ensemble of LBP features is compared with the original and Haar-like features on a face detection task using CMU-MIT frontal face test set [17], on a car detection task using UIUC multiscale test [1] and on a gender recognition task using FERET dataset [16].

The paper is structured as follows. Section 2 introduces local binary patterns methodology and its modifications. In this section we also introduce two new encoding rules for binary code generation. Experimental validation and comparison of our extensions are presented in Section 3 and the paper is concluded in Section 4.

2 Local Binary Pattern and its modifications

Local binary patterns have gone through a large number of changes and adjustments, which lead to generalization or improvement of some of their specific characteristics. The changes can be viewed from several perspectives. In Section 2.1, changes from the perspective of the measurement processes are reviewed. Next, in Section 2.2, we look at encoding method for the measurements. Finally, in Section 2.3, two novel encoding methods are introduced.

2.1 What is measured

The local binary pattern [14] operator, also known as census transform [24], is a non-parametric gray-scale descriptor invariant to monotonic transformations of the intensity function. The basic version of LBP considers measurements from a 3x3 pixel square.

The binary code that describes the local texture pattern is obtained by thresholding the eight neighborhood pixel values by the gray value of the center, see Figure 1(a). The operator was extended to rotation symmetric and multiscale version [15], see Figure 1(b). This version of the LBP is
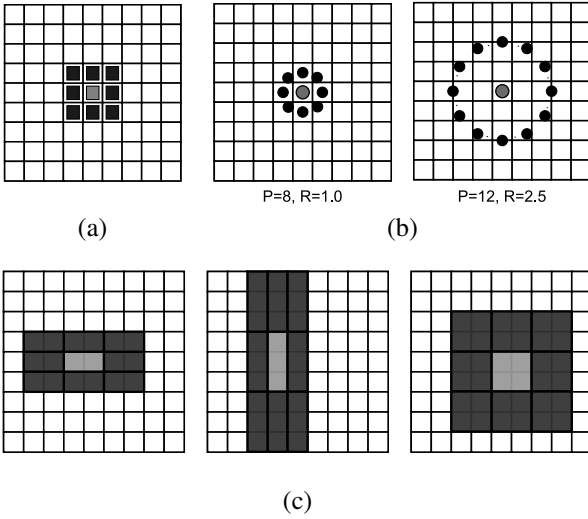
Figure 1: LBP comparison values: (a) original LBP (b) rotation symmetric and multiscale $LBP_{P,R}$ (c) Examples of multi-block local binary pattern (MB-LBP)
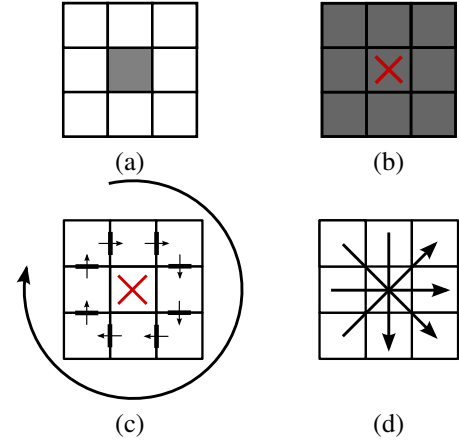

Figure 2: Extended set of LBPs: (a) conventional LBP thresholded by center pixel value; (b) 8-bit coded modified LBP (mLBP) thresholded by pixels mean value; (c) transition coded LBP (tLBP),see Eq.(2); (d) direction coded LBP, see Eq. (3);

parametrized by the neighborhood size P and the radius R and is defined as

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, \qquad (1)$$

where

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases},$$

g_p are gray values of pixels regularly spaced on circle and g_c is the gray value of the center pixel. Gray values at non-integer positions are obtained by interpolation. Another encoding, the LGBP, was introduced by Zhang at al. [27], who calculate LBPs on images preprocessed with Gabor wavelets.

All the LBPs described above are commonly used in conjunction with classification of distributions (histograms), calculated in a semi-local neighbourhood. In detection and recognition approaches exploiting spatial appearance of features, single LBP measurements are unstable and sensitive to noise and localization. The problem was addressed by Zhang at al., who introduced a Multi-Block LBP (MB-LBP) [26], which is inspired by Haar features [22]. Instead of comparing pixel values, Zhang compares mean values of 3x3 adjacent rectangular blocks, which can be done in constant time using the integral image [22].

The MB-LBPs enable generating large sets of operators with different scales and aspect ratios, see Figure 1(c). Similarly to Haar features, integrating larger areas makes the measurements more stable and suitable for spatial appearance classification methods. However, this modification does not possess LBP's invariance to monotonic intensity transformations, only invariance to affine intensity changes is preserved. The MB-LBP feature also appears in the literature as the Locally Assembled Binary (LAB) feature [23].

2.2 Encoding methods
Improvements of LBP aimed at modifying the resulting binary code started with the rotation symmetric and multiscale

LBPs of Ojala [15]. The rotation invariant encodings, denoted $LBP_{P,R}^{ri}$ (which can be found also as Advanced LBP - $ALBP_{P,R}$ [10]), are restricted to a subset of so-called "uniform" patterns ($LBP_{P,R}^{riu2}$).

Froba at al. introduced a modified census transform [4], which was adopted also as a modified LBP (mLBP) [21]. The Modified LBP uses the mean value of all measured pixels as a threshold, so the final code then generates $2^9 - 1 = 511$ unique values instead of $2^8 = 256$ of LBP codes. Because of compatibility with the original LBP, we adopted only code generated by eight border pixels with 2^8 unique values, see Figure 2(b). Heikkilä at al. in [6] introduced a center symmetric LBP (CS-LBP) modification for description of interest regions. Their rule encodes the sign of the difference of two border pixels symmetrically placed due to the center, thus the final code of CS-LBP generates $2^4 = 32$ unique codes.

2.3 The novel encoding methods
To introduce new encoding rules we were motivated by spatial appearance classification models, which enables to effectively combine different features. The evaluation complexity of the model does not increase, provided that the computation cost of each feature is approximately equal. Extension of the feature set from which the features are chosen increase only training time but not the evaluation time. This lead us to propose encoding rules, which should not be competitive with LBP but complementary and extend a set of feature candidates. In order to preserve compatibility with LBP, we set the restriction on dimension of generated binary code to be the same as the original.

Transition Local Binary Patterns (tLBP) - The LBP encoding rule thresholds the neighbor gray values by its center pixel value. This gives rough knowledge of pixel with respect to the center one, but relations between pixels with the same binary value are lost. Binary value of transition coded LBP is composed of neighbor pixel comparisons in clockwise direction for all pixels except the central, see figure 2(c). Thus this rule encodes relation between neighbor pixels. It can be
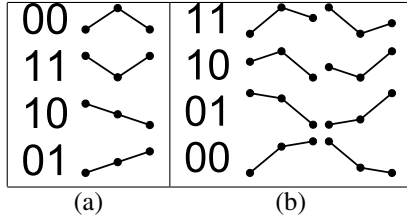
Figure 3: Examples of generated codes and schemes of possible pixel intensity values for a given pixel sequence: (a) LBP encoding rule, (b) dLBP encoding rule

also seen as an information about partial ordering of border pixels. Each sequence of the same binary values indicates ordered sequence of pixel intensities.

More precisely, let g_p correspond to gray value p-th neighbor of center pixel, then

$$tLBP_{P,R} = s(g_0 - g_{P-1}) + \sum_{p=1}^{P-1} s(g_p - g_{p-1})2^p. \quad (2)$$

We can see that tLBP is gray-scale invariant and can also benefit from rotation invariant extension and uniform extension of LBP ($LBP_{P,R}^{riu}$).

Direction coded Local Binary Pattern (dLBP) - Motivation of dLBP is to provide better information of local pattern in sense of direction functions similarly to CS-LBP. For simplicity, let us consider the basic LBP operator. We can see that there are four base directions through the center pixel in LBP, see Figure 2(d). We encode intensity variation along these directions into two bits, thus the binary word has the same length as the original LBP. In contrast to the CS-LBP, we also use center pixel information for encoding. The first bit encodes, whether the center pixel is an extrema and the second bit encodes, whether the difference of border pixels due to the center one grows or falls. In Figure 3 we can see comparison of LBP and dLBP rules for a given direction. Both the LBP and the dLBP rules encodes if center pixel is an extrema. Unlike the LBP rule, the dLBP does not encode it as maximum or minimum but encodes if sign of first and second differential is the same. This gives to the dLBP not only gray-scale intensity invariance property, but also the intensity inversion invariance property.

Formally, let $LBP_{P,R}$ have $P = 2P'$ neighbors, then

$$dLBP_{P,R} = \sum_{p'=0}^{P'-1} \Big(s(g_{p'} - g_c)(g_{p'+P'} - g_c)2^{2p'} + s(|g_{p'} - g_c| - |g_{p'+P'} - g_c|)2^{2p'+1} \Big) \quad (3)$$

3 Experiments

In all the detection and classification experiments, only the multi-block extensions of LBP were evaluated as they have outperformed the standard LBP. The extended MB-LBP set (EMB-LBP) included the MB-LBP, mMB-LB, tMB-LBP and dMB-LBP, see Figure 2(a-d).

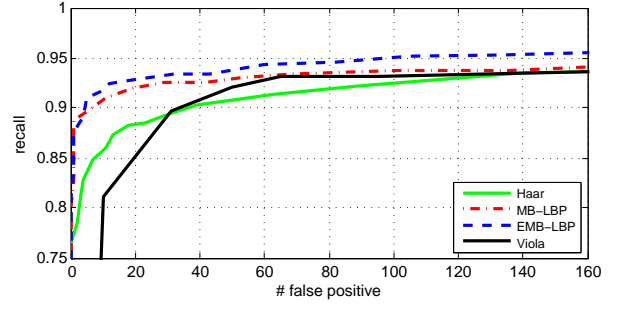The tests evaluated performance of different LBP types in the process of boosting a detector (or a classifier). The

Figure 4: Frontal face detection - The ROC curve on the CMU-MIT data set

Figure 5: Some detection results on the CMU-MIT data set

EMB-LBP set was tested on face and car detection tasks using the WaldBoost[19] detector and on gender recognition task using AdaBoost classifier. The reason is that for gender recognition, speed of the classifier is not important as only one window per face is classified. On the other hand, in the car and face detection problems, hundreds of thousands of windows are evaluated and speed, the main advantage of WaldBoost over AdaBoost, is a critical parameter.

WaldBoost is an AdaBoost-based algorithm which automatically builds a fine-grained detection cascade of the Viola and Jones type [22] based on Wald's sequential probability ratio test (SPRT). The training runs in loops, the first iteration is a standard AdaBoost learning search for the best weak classifier. Then the Wald's thresholds are estimated on a large pool of data (we used 20.10^9 samples). After that, the pool is pruned and bootstrap strategy is used to collect non-object examples. To speed-up the AdaBoost learning step, a smaller set was sampled from the pool using QWS+ strategy [8]. The weak classifiers are build on MB-LBPs by estimating the weighted error for each code as in the confidence-rated classification approach [18], which enables a fast look-up table based implementation.

In all experiments, three classifiers were trained. The first was learned with Haar features (including six types of features ▮▮ ▮▮ ▬ ▯▯ ◣ ▪), the second with MB-LBP features and the third one with the EMB-LBP feature set.
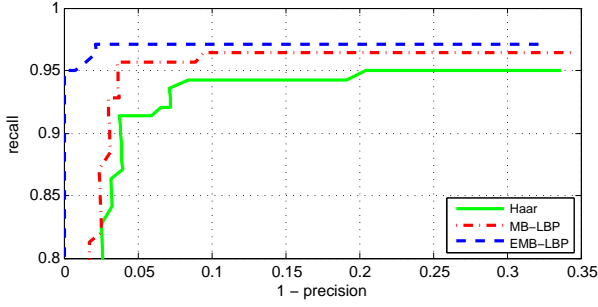
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Figure 6: Car detection - The recall-precision curve on the UIUC car data set

method	recall
Agarwal at al. [1]	39.6%
Fritz at al.[5]	87.8%
Mutch at al.[13]	90.6%
Lampert at al.[9]	98.6%
WaldBoost, Haar[1]	91.4%
WaldBoost, MB-LBP[1]	95.7%
WaldBoost, EMB-LBP[1]	97.1%

[1] our implementation

Table 1: Recalls on the UIUC Car dataset at the point of equal precision and recall.

3.1 Face detection

The face detectors were trained on 5500 face images and on more than 3000 background images. We set the minimum resolution of the detector to 24x24 pixels and its length to 1000 weak classifiers. SPRT parameters were set to allow 10% false negative rate and no false positives on the training data.

The detectors were tested on standard the CMU-MIT frontal face database [17], which consists of 130 images with 507 labeled frontal faces. Some detection results can be seen at Figure 5. The ROC curves for the three detectors are shown in Figure 4. The detector using the EMB-LBP feature set slightly improves recall for all levels of false positive rates.

3.2 Car detection

The side car detection performance is evaluated on the UIUC car dataset [1], which consists of 550 positive training samples and the multi-scale and the single-scale test sets. We
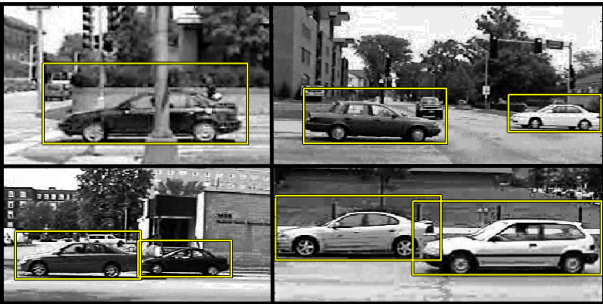

Figure 7: A samples of detection results on the UIUC Car set

Training algorithm	face size	trn/tst[1]	Accuracy
AdaBoost, pixel comparison [3]	20x20	YES	94.4%
SVM (RBF) [3]	20x20	YES	93.5%
SVM (RBF) [12]	20x20	NO	96.6%
AdaBoost, LBP[20]	120x144	?	95.7%
AdaBoost, Haar[2]	20x20	YES	92.4%
AdaBoost, MB-LBP[2]	20x20	YES	93.8%
AdaBoost, EMB-LBP[2]	20x20	YES	94.6%

[1] each person in the data set is included only either in the training or test set
[2] our implementation

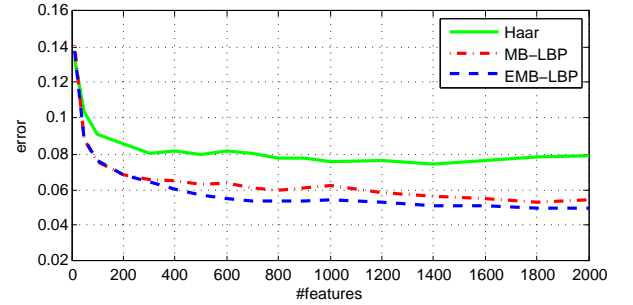**Table 2:** FERET dataset - gender classification accuracy

Figure 8: Gender recognition: mean cross validation error as a function of classifier length (i.e. the number of features)

trained the detectors on 16x40 pixels windows and allowed 5% false negative rate on the training set; classifier length was set to 500 features.

For the experiment, we chose the multi-scale test set, which consists of 108 images containing 139 car side views. The set includes instances of partially occluded cars, cars that have low contrast with the background, and images with highly textured backgrounds. Sample detection results are displayed in Figure 7.

As is common for the UIUC Car dataset, we measure the performance by the 1-precision vs. recall curve. Figure 6 shows the curves for different feature sets. The detector using EMB-LBP feature set improves recall for all levels of precision and dominates both MB-LBP features to Haar features. The difference in performance is impressive for high precisions where a recall of 95% was achieved with 100% precision. Table 1 compares recalls at the point of equal precision and recall with the state-of-art results. The EMB-LBP is highly competitive.

3.3 Gender recognition

The gender recognition experiment was carried out on the Feret data set [16], which is a standard data set for face recognition task and has also been used as a gender recognition benchmark data set. Data set contains several photos of persons with different pose; we used only frontal images labeled "fa" and "fb" in the database. The dataset includes 1006 persons (599 males, 407 females). For evaluation, we adopted Baluja's methodology [3] which uses 5-fold cross validation. Each partition splits the training and testing data 80:20 in such a way that each individual appears only in the training set or the test set. It is important to note that Moghaddam at
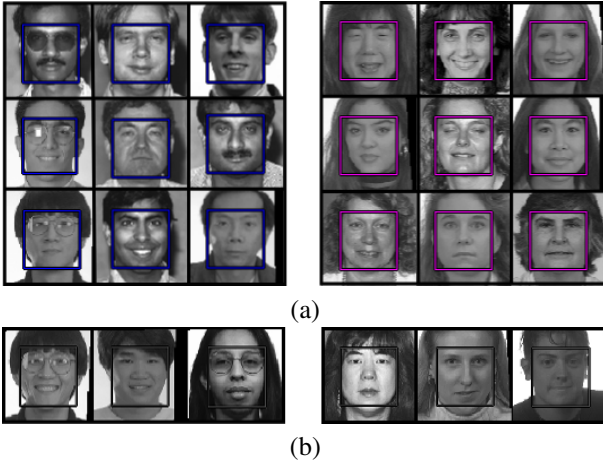
(a)

(b)

Figure 9: Examples of correct (a) and wrong (b) classification of sex between men (left) and women on the FERET dataset. Note that gender classification for images showed in (b) is difficult even for humans.
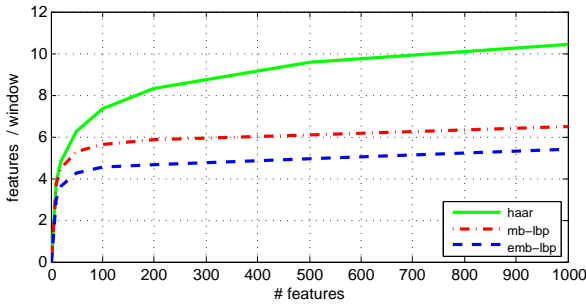

Figure 10: Frontal face detection - the average number of used features per scanning position

al. [12] split the data so that images of a the same individual appears both in the training and the test set. This is important, because when persons are mixed in sets, the resulting gender classifier has a tendency "remember" individuals and their gender.

The training set contained 2350 faces (1500 males, 850 females) and the test set contained 600 faces (380 males, 210 females). We have trained five AdaBoost classifiers with enlarged data set using small face alignment perturbations to enlarge collected data 20 times. For AdaBoost, learning we sampled 5000 males and 5000 females using QWS+ sampling strategy. The length of learned classifiers was set to 2000 features.

The average accuracy on cross validation test sets is displayed in Table 2 (the table contains results for classifiers of length 1000 features for comparison with [3]). Dependence of mean cross validation error due to the length of the classifier is displayed in Figure 8. The EMB-LBP improves MB-LBP classifiers and achieves results comparable to the state-of-art results.

3.4 Speed comparison

For both detection tasks (faces, cars) the average number of evaluated features per scanning window position was measured. The average number of evaluated features is a pre-
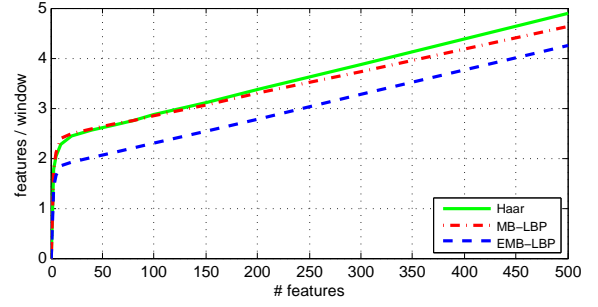

Figure 11: Car detection - average number of features used per scanning position

		LBP			
	Haar	MB	mMB	tMB	dMB
Haar	1.000	1.114	1.117	1.207	1.242
MB-LBP	0.898	1.000	1.003	1.011	1.114

Table 3: Comparison of the relative feature evaluation time

cise predictor of running time. Dependences of the number of evaluated features on the detector length are displayed in Figures 10 and 11. The face detectors were set up very much like the Viola's cascade in terms of accuracy and speed, see Haar-like detector. (Viola's detector uses an average of 10 feature evaluations per scanning window.) Therefore, it is clear that EMB-LBP feature set improves both the accuracy and detection speed, which is nearly two times faster than Haar-like detector in terms of feature evaluation.

It may be expected that calculation time of xMB-LBPs can be longer than for Haar-like features. Therefore we measured evaluation time of 10000 randomly generated features on 10000 image patches for sets of Haar-like, MB-LBP, mMB-LBP, tMB-LBP and dMB-LBP features. Table 3 shows the relative time cost of our implementation of features w.r.t. Haar-like features (line 1) and to MB-LBP features (line 2). We see that the acceleration in the case of face detection is still at least one-third.

3.5 Feature preferences

AdaBoost learning algorithm can bee seen also as a benchmark tool for feature strength comparison, if the same classifier is used. It uses greedy approach to minimize training error and at each stage chooses the best weak classifiers. Thus, frequency of feature selection indicates how often a given feature dominates the others. However, it does not show how much better than the other it was. Dependence of feature selection on the length of classifier is shown in Figure 12. It can be seen that for different tasks the ratio of representation of features differs significantly. For face detection the contribution of dMB-LBP features are negligible, but they dominate others for gender recognition. The standard MB-LBP features [26] perform surprisingly poorly and as Figure 12 shows for car side detection they were not used at all.

4 Conclusions

Two new encodings of LBPs have been presented. We have trained spatial appearance models based on multi-block mea-

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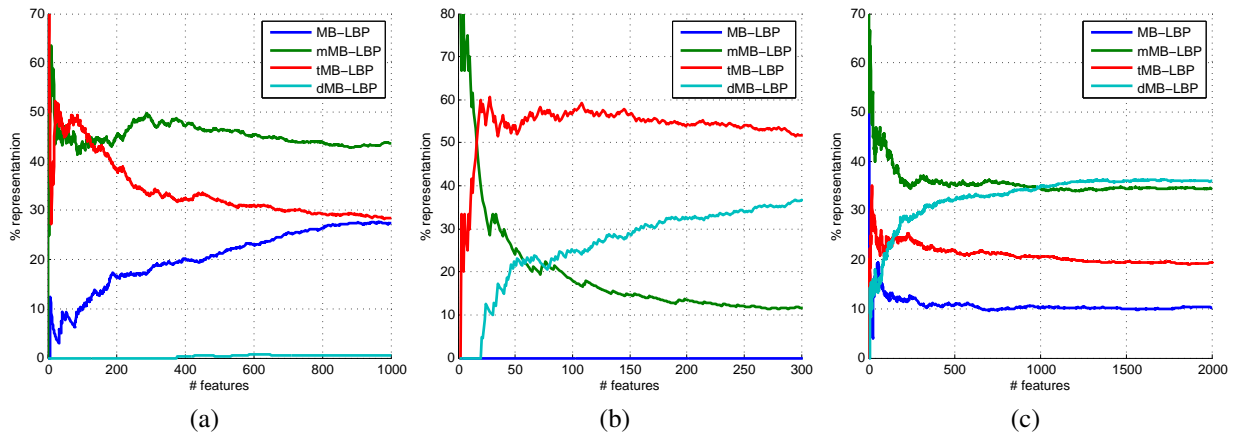
MB . . . multi-block measure of gray values, see Sec. 2.1
LBP . . . original LBP encoding rule, Eq. 1
mLBP . . . modified LBP encoding rule, mean of gray values is used instead of the center
tLBP . . . transition LBP encoding rule, Eq. 2
dLBP . . . direction LBP encoding rule, Eq. 3

Figure 12: EMB-LBP feature representation: (a) Face detector, (b) Car side detector, (c) Gender classifier.

surements of LBP. Instead of direct comparison of every new rule with other LBP methodologies, we have used a trained classifiers using an ensemble of different LBP encoding rules. In experiments we have made comparisons with standard LBP encoding rule and traditional Haar features. We have tested detectors based on the extended set of LBP features on the CMU-MIT frontal face data set and on the UIUC car side data set. Experiments on gender recognition task used the Feret dataset. In all cases, the extended set of LBP features dominates both the LBP features and Haar features. For the detection tasks, the proposed LBP set has improved speed of learned detectors, in case of the face detection task almost two times. The price paid for achieved improvements of the detectors and classifiers has been only the increase in the training time. In experiments we have shown that the importance each of the encoding rules depends on the task and there is no dominant rule.

Acknowledgement

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