# BGLBP-based Image Background Extraction Method

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**Abstract**: Local Binary Pattern (LBP) is invariant to the monotonic changes in the grey scale domain. This property enables LBP to present a texture descriptor that can be useful in applications dealing with the local illumination changes. However, the existing versions of LBP are not able to handle image illumination changes, especially in outdoor environments. These non-patterned illumination changes disturb performance of the background extraction methods. In this paper, an extended version of LBP which is called Back Ground Local Binary Pattern (BGLBP) is presented. BGLBP is designed for the background extraction application but it is extendable to the other areas as a texture descriptor. BGLBP is an extension of Direction LBP (D-LBP), Centre-Symmetric LBP (CS-LBP), Uniform Local Binary Pattern (ULBP), and RIU-LBP (Rotation-Invariant Uniform LBP) and it has been designed to inherit the positive properties of previous versions. The performance of BGLBP as a part of background extraction method is investigated.

Keywords: Texture descriptor, LBP, background extraction.

Received September 10, 2014; accepted September 20, 2015

#### **1. Introduction**

Local Binary Pattern (LBP) can be used in the background extraction process. The intensity of an image is multiplication of the illumination and the reflectance. The illumination changes cause unpredictable intensity values and result in an unexpected image difference in the background subtraction process. This occurrence interferes with the accuracy of the motion detection process [17]. Recently, LBP has been used to describe pixel properties. The basic principle of LBP, as a texture descriptor, is a scene which is seen as a composition of micro-patterns generated by a concatenation of circular binary gradients [21]. The histogram of these illumination invariant micro-patterns is used as a behaviour descriptor of the corresponding pixel, block or region.

LBP is invariant to monotonic changes in the grey scale domain [6, 16] and an LBP histogram does not present information about the positions where the individual LBP codes have been calculated. These properties make LBP histograms robust against illumination changes. LBP histograms also support multi-modal backgrounds. They are computationally fast. Furthermore, more than one LBP histogram can be used to model each block [6].

Our experiments show that manipulating the definition of LBP and its calculation method increases its description power to describe the changes of pixel intensity, especially when illumination changes are large and take place quickly. These experiments led us to introduce an extended version of LBP called Back

Ground Local Binary Pattern (BGLBP). Due to these characteristics of BGLBP, LBP is therefore effective in other applications as a powerful texture descriptor.

In this paper, the performance of BGLBP is investigated in two different aspects. First, a comparison between BGLBP and a number of other versions of LBP is undertaken. Furthermore, the effect of BGLBP is evaluated on the background extraction application.

The remainder of this paper is organized as follows. Section 2 presents a review of existing versions of LBP, whereas section 3 presents our proposed BGLBP. Section 4 discusses the performance of the BGLBP in background extraction application. Finally, the material presented throughout the paper is summarized in section 5.

## 2. Local Binary Pattern

LBP was first introduced in 1994 [13]. A LBP operator offers an effective way of analysing textures. LBP is simple and combines the properties of structural and statistical texture analysis methods. It is invariant to monotonic grey-scale changes. The original version of LBP is calculated according to the following formula:

$$LBP_{R,N}(x, y) = \sum_{i=1}^{N-1} s(p_i - p_c) \times 2^i$$
 (1)

Where  $p_c$  and  $p_i$  stand for grey values of the central pixel and each neighbour pixel of N is an equally spaced pixel on a circular path of radius R, respectively. The function s(x) is defined as follows:

$$s(x) = \begin{cases} 1 & x \ge 0\\ 0 & otherwise \end{cases}$$
(2)

LBP can be calculated for each block separately. Xia *et al.* [18], to calculate the LBP value of each block Multi-Block Local Binary Pattern (MB-LBP), an operator is defined by comparing the average intensity of the central block with its neighbour blocks.

The Centre-Symmetric Local Binary Pattern (CS-LBP), which was first used for matching and objectcategory classification is an effective extension of LBP [5]. This operator is illumination invariant, more robust to noise, and it produces short histograms. Another improved version of CS-LBP is presented by [20]. This operator classifies the local pattern based on relativity of the central pixel and the centre-symmetric pixels instead of the grey value differences between the centre-symmetric pixels. The author has named their method Direction Local Binary Pattern (D-LBP). No thresholds are needed in D-LBP; it is difficult to choose the adaptable threshold in CS-LBP [7].

Uniform Local Binary Pattern (ULBP) is an extension of the original LBP. ULBP reduces the feature dimensions and increases the noise immunity. ULBPs include most of the LBPs and hence all the non-uniform LBPs are usually gathered into one single bin of the LBP diagram. This feature reduces the number of bins and enhances the classification efficiency [4]. ULBP is an LBP that contains at least two bitwise 0-1 or 1-0 transitions. Lun *et al.* [11] extended the original LBP feature and proposed the MB-LBP, which is motivated by using Harr-like features.

## **3. Back Ground Local Binary Pattern: A** New Version of Local Binary Pattern

Two critical properties are required for a desired LBP version in the background extraction.

- 1. It should be fast and the number of bins in the plotted histogram should be the least.
- 2. It should be calculated based on whole pixels values belonging to each block.

Therefore, the original LBP, LTP, and the gradient LBP are not recommended. The MB-LBP calculates a LBP value for each block instead of each pixel separately. It is calculated exactly based on the minimum, average, maximum or an approximate value of the pixels belonging to the corresponding block. Working on these derived values reduces the sensitivity to the level of illumination changes and this version of LBP is not recommended for background extraction. ULBP is not rotation invariant and finally there are many bins in the CS-LBP model. Regarding all of these limitations, BGLBP is introduced in this paper in order to overcome these problems.

BGLBP is calculated according to the following equations:

$$BTGLBTP_{P,R}^{id} = \begin{cases} \left(\frac{P}{2}\right)^{-1} & \sum_{i=0}^{\infty} s_{id} \left(g_{i}, m, g_{\left(\frac{P}{2}\right)+i}\right) \times 2^{i} & U(LBP_{P,R}) \le 2 \end{cases}$$
(3)

Otherwise,

$$s_{id}\left(g_{i}, m, g_{\left(\frac{P}{2}\right)+i}\right) = \begin{cases} 1 & if \left( \left(g_{i} \ge m \ge g_{\left(\frac{P}{2}\right)+i}\right) \\ \| \left(g_{i} \le m \le g_{\left(\frac{P}{2}\right)+i}\right) \right) \\ \\ & \left(g_{i} \le m \le g_{\left(\frac{P}{2}\right)+i}\right) \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} \right) \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} \right) \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} \right) \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} + g_{i} \right) \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} + g_{i} \right) \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} + g_{i} + g_{i} + g_{i} + g_{i} + g_{i} \\ \\ & \left(g_{i} \le m \le g_{i} + g_{i} \\ \\ & \left(g_{i} \le g_{i} + g_{i} \\ \\ & \left(g_{i} \le g_{i} + g_{i} \\ \\ & \left(g_{i} \le g_{i} + g_{i} \\ \\ & \left(g_{i} \le g_{i} + g_{i} \\ \\ & \left(g_{i} \ge g_{i} + g_{i$$

Otherwise,

$$m = \frac{1}{P} \left( g_c + \sum_{i=1}^{P-1} g_i \right)$$
 (5)

 $g_i$  (*i*=0, ..., *i*=*P*-1) corresponds to the grey values of *P* equally spaced pixels on a circular path of radius *R* that forms a circular symmetric neighbour set.  $g_c$  presents the intensity value of the central pixel, U refers to a uniform pattern, and id is an identifier for the block.

In this formula, first, the average of local intensity values is calculated in Equation 5. The average value is used as an intensity threshold value to detect the changes in the neighbour pixels. This is used to reduce the noise. Equation 4 detects the intensity changes of ith pixel when the pixel's intensity value is more than the average value and the average value is more than intensity value of the corresponding diagonal pixel or when the pixel's intensity value is less than the average value and the average value is less than the intensity value of the corresponding diagonal pixel. Furthermore, the difference between these changes is more than  $\beta$ . Using the earlier condition, the small illumination changes in the image are disregarded. This helps to detect large changes more appropriately. Since the summation of two different values is utilized with the same minimum values, the difference is regarded as an illumination change in the BGLBP. The threshold  $\beta$  in Equation 4 is set to 3 from the experiments shown in Table 1. This table explains the impact of minimum distance difference values on the accuracy of the extracted background image. Using Equation 3 half the changes of the uniform neighbour pixels are accounted. A pattern is uniform if the number of the corresponding changed bits is less than or equal to 2.

Table 1. Impact of different min distance threshold values using the Shopping Mall (SM) dataset.

Min Distance Threshold	Time (ms)	FDR (pixels)	X <sup>2</sup>	PSNR	RMS (pixels)
1	72.12	21180	26465	20.7284	161,172,246
2	74.21	21174	26452	20.7297	161,151,259
3	76.76	21165	26433	20.7309	161,127,310
4	76.877	21169	26423	20.7309	161,125,389
5	76.70	21172	26418	20.7307	161,128,531

BGLBP gains the advantages of other LBP versions.

- The time and memory complexity of BGLBP is less than the LBP. Since BGLBP is based on ULBP, the number of bins is much less than the number of bins in the LBP ( $\log_2^n + \log n \log_2^n + \log n$ ). BGLBP needs less memory and less time to calculate the histogram. However, computing the number of Uniform LBPs is time consuming. Overall, the time complexity of BGLBP is less but its time consumption is not.
- BGLBP is not noise sensitive. The BGLBP histogram is calculated for each block. The noise which is applied to a number of pixels in the block hardly affects the performance of the decision, which is made based on the calculated BGLBP histogram. In addition, to calculate the BGLBP for each pixel, average of the intensity values of the corresponding pixel and its neighbour pixels is calculated and used. Using the average value makes the BGLBP less sensitive to noise. Moreover, small changes are not considered in the BGLBP so that small noises are omitted.
- BGLBP is local Rotation Invariant (RI) because it is based on RI-LBP. There is no priority between neighbour pixels, which are located on a diagonal around the central pixel. Since RI-LBP is basically introduced to present a rotation invariant version of LBP, it can be taken that the BGLBP is also local rotation invariant.
- To calculate the BGLBP histogram, the mean value of the background Gaussian model (temporal information) and the spatial information is used. Using temporal information in BGLBP causes sensitivity to any occurring gradual illumination changes in each pixel and in each block from time to time.
- Updated BGLBP histogram is more sensitive to large intensity changes.
- BGLBP can disregard the small illumination changes in the image and help to detect large changes more appropriately. At the first view, combination of these two opposite properties is not possible. Using blocking makes able background extraction method to neglect small changes. A block to be detected as a moving block should have a minimum number of pixels with different illumination values; a small number of changed pixels is less than the required minimum threshold value thus small changes are neglected. On the other hand, in calculation of the BGLBP histogram for each block, Equation 6, big illumination changes occurring in the sudden changes, for example when a vehicle with completely different gray values is entered to the scene, are counted two times. It means blocks including pixels with big different gray values are detected as the moving blocks. Therefore the algorithm is sensitive to the sudden illumination changes.

In addition, the histogram calculation method is changed in order to apply the effect of large changes in the intensity values of each pixel in any block. If the difference between the average intensity values of the neighbour pixels and its corresponding mean value of the background Gaussian model is larger than a predefined threshold, the corresponding bin of the calculated BGLBP is increased by 2, otherwise it is increased by 1. This technique causes the BGLBP to be more robust against unexpected illumination changes.

$$\operatorname{Bin}_{i}^{\operatorname{BGLBP}}_{i} + = \begin{cases} 2 & |m - \mu_{g_{e}}| \ge T \\ 1 & otherwise \end{cases}$$
(6)

Where  $\mu_{gc}$  stands for the mean value of the background Gaussian model in the corresponding pixel. *T* is a threshold which is calculated experimentally.

In order to estimate the above threshold, SM as a crowded indoor environment and Pets2000 (P0) as a semi static outdoor scene were selected and different threshold values in two image sequences were investigated. For each dataset, an image from the dataset including no object is manually selected as the ground truth image. The results are shown in Tables 2 and 3. In these two tables, the desired factors are calculated using different values of T. A range between 0 and 255 has been assigned to the threshold and the best results are achieved between 40 and 80. Finally, 75 is assigned to the threshold value. This value is constant in the rest of the image sequences.

Table 2. Impact of different values of the T parameter using SM dataset.

Т	Time (ms)	FDR (pixels)	$\mathbf{X}^2$	PSNR	RMS (pixels)
40	77.79	21,190	26,422	20.7291	161,183,338
50	76.48	21,175	26,416	20.7303	161,152,620
60	75.63	21,177	26,419	20.7306	161,141,863
65	75.60	21,172	26,420	20.731	161,128,332
70	76.89	21,170	26,430	20.731	161,126,955
75	75.82	21,165	26,433	20.731	161,127,310
80	75.65	21,170	26,443	20.7303	161,128,417
90	75.81	21,172	26,449	20.7297	161,141,734
100	75.17	21,180	26,454	20.729	161,163,767

Table 3. Impact of different values of the T parameter using the PETS2000 (P0) dataset.

Т	Time(ms)	FDR(pixels)	<b>X</b> <sup>2</sup>	PSNR	RMS(pixels)
40	108.32	5,502	89,224	19.5566	114,029,939
50	107.87	5,502	89,228	19.5565	114,036,089
60	107.88	5,503	89,228	19.5566	114,029,464
65	106.78	5,503	89,233	19.5566	114,028,934
70	106.65	5,503	89,233	19.5566	114,027,994
75	98.09	5,501	89,211	19.5581	114,019,061
80	107.72	5,501	89,228	19.5567	114,025,002
90	106.64	5,503	89,236	19.5568	114,014,062
100	106.63	5,502	89,238	19.5567	114,017,954

$$\theta = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} \left( BG(x, y) - GT(x, y) \right)^{2}$$
(7)

Where, M and N are dimensions of the current image; and BG refers to the extracted background image and GT denotes the ground truth image. • It is possible to calculate the mean distance of the patterns belonging to a cluster because of the k-way partitioning [9, 10]. The mean distance is regarded as an indicator of cluster homogeneity. This factor is calculated according to the Equation 8.

$$X^{2}(S,T) = \sum_{i} \frac{(BG(i) - GT(i))^{2}}{(BG(i) + GT(i))^{2}}$$
(8)

- The False Detection Rate (FDR) is the fourth quantitative  $\beta$  factor, which is used in this research.
- Finally, as the last quantitative factor, the Peak Signal to Noise Ratio (PSNR) is calculated and defined as Equation 9:

$$PSNR = 10\log_{10}\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(BG(i,j))^{2}}{\sum_{i=1}^{M}\sum_{j=1}^{N}(GT(i,j) - BG(i,j))^{2}}\right)$$
(9)

#### **3.1. Back Ground Local Binary Pattern vs.** Other Versions of Local Binary Pattern

As it was mentioned before, BGLBP is used as a part of a background extraction method. In addition, BGLBP is introduced to enhance the sensitivity of LBP when it is faced with intensity changes. In this section, the performance of the BGLBP as a part of a background extraction method is investigated in comparison with the other versions of LBP.

Among the numerous versions of LBP, the following versions of LBP are selected and re-implemented in this research, namely, original LBP, circular LBP, ULBP, Improved Centre-Symmetric Local Binary Pattern (ICS-LBP) [20], Improved Direction Local Binary Pattern (ID-LBP) [7], Rotation Invariant Uniform Local Binary Pattern (RIU-LBP) [12], MB-LBP, and Circular Multi-Block Local Binary Pattern (CMB-LBP). The methods are analysed using the P0 [15] and SM [14] image sequences. These two datasets are selected as sparse and crowded scenes, respectively. For the background extraction method, the proposed method in [3] is used. The experiments are done with and without the initialization process and the results are presented in Tables 4 and 5 respectively. The results show that the desired factors have more acceptable values after applying BGLBP compared to other LBP versions. If the initializing method is also applied, the results of the background extraction method including BGLBP are more accurate.

Table 4. Performance of each LBP version using the SM dataset with initialization.

Method	Time(ms)	FDR(pixels)	$X^2$	PSNR	RMS (pixels)
Original LBP	70.83	21220	26349	20.7299	161,260,665
MB Block	58.40	21228	26468	20.7235	161,279,805
CMB Block	40.87	21250	26575	20.7171	161,392,293
ULPB	70.87	21219	26372	20.7285	161,256,899
ICS-LBP	63.58	21210	26379	20.73	161,210,903
ID-LBP	71.52	21212	26365	20.7305	161,214,102
RIU-LBP	74.15	21208	26398	20.7278	161221927
Circular LBP	62.14	21207	26410	20.7264	161,238,948
BGLBP	89.93	21156	26307	20.7365	161,208,067

Table 5. Performance of each LBP version using the SM dataset without Initialization.

Method	Time(ms)	FDR(pixels)	$X^2$	PSNR	RMS(pixels)
Original LBP	72.04	22332	34292	20.295	167,469,610
MB Block	58.95	22303	34406	20.2886	167,486,171
CMB Block	41.53	22301	34556	20.2816	167,571,330
ULPB	53.29	22285	34465	20.2866	167,483,899
ICS-LBP	64.41	22309	34294	20.2962	167,419,353
ID-LBP	72.834	22306	34300	20.2946	167,426,883
RIU-LBP	73.15	22310	34299	20.2944	167,428,572
Circular LBP	62.36	22304	34333	20.2921	167,437,950
BGLBP	91.37	22255	34251	20.2962	167,409,619

It is clear that the improvement of the results is not significant. This is due to two reasons: First, desired factors are obtained by averaging over a number of blocks. These blocks belong to a sequence of frames. Events such as sudden changes in the intensity, rotation, entrance of objects, objects leaving the scene, and the movements of moving objects affect the performance of different LBP methods. It is clear that the average value of the desired factors cannot highlight these effects in detail. In addition, the efficiency of the methods such as the evolutionary algorithms and the history-based methods do not appear in a short time. Since the utilized background extraction method is a history-based method, it is not logical to expect a significant improvement. Second, in this research, the LBP descriptor is not used to describe the details of the texture. LBP is only used to help the system to distinguish the background blocks from the foreground blocks. This means that the enhancement of the LBP version does not have a significant effect on the extracted background.

## 3.2. Analysis of Ground Local Binary Pattern in the Background Image Extraction Application

This experiment is done to investigate the performance of our background extraction method, which is presented in [2] using BGLBP. Overall, the following steps are applied in this experiment:

- The background is initialized using the proposed initialization method in [3].
- Each frame is divided into a number of nonoverlapped blocks.
- BGLBP is calculated for each pixel.
- Each block of the current frame is classified as a foreground block or a background block according to the history of each block and using a history-based method. Historical information of each block is a set of the BGLBP histograms.
- If a block is detected as background, the model's history should be updated. Otherwise, it should be determined whether each pixel in the block is a foreground pixel or a background pixel. For this purpose, a mixture of Gaussian model is used. According to the number of detected foreground

pixels, the block is categorized again as a foreground block or a background block.

- An adapted method is used to update the history of pixels and blocks depending on whether they were detected as a background or a foreground.
- Moving pixels are identified.
- A simple method is used to extract the final background image.
- X2, FDR, PSNR, and RMS form the desired factors of the experiment. These values are calculated from the extracted background image.
- The results are compared with three recent methods [1, 8, 19].

Table 5 provides a brief view of the results. The method is repeated using the other versions of LBP. A comparison between the first row, which is the results of the BGLBP and the second row as the best ever achieved results shows the increscent of the results in BGLBP. The values that arise from comparing the first row and the average of rows 3 to 5 are 16 %, 5 %, 1.8 %, and 7.7 %, respectively.

In addition, in order to evaluate qualitatively the resulted background extraction image by applying BGLBP, a number of tests are conducted. In each experiment, a specific kind of illumination change is raised and it is shown that the proposed method is able to overcome these problems.

#### 3.2.1. Moving Objects in the First Frame

Sometimes there is a moving object in the first frame and when the history of background model is being initialized it is expected that the method detects the moving object and removes it from the extracted background. In order to assess the performance of the proposed method in this state, a test using PETS 2000 (P0) dataset is done. As it is clear in Figure 1, the proposed method has detected and removed the pedestrian in the top left corner of the first frame.



Figure 1. Detecting primary moving object by the proposed method using PETS2000 from 780th frame to 1280<sup>th</sup>.

#### **3.2.2.** Static Objects are added to the Scene

Sometimes an entered moving object stops in the frame sequence. After being stable for a period, the method should detect this object as a part of the extracted background. Clearly, it is not possible to detect the object immediately; usually this section of the background image is constructed evolutionarily and pixel by pixel or block by block. In addition, methods adapt the intensity value of remaining object pixels gradually. The construction speed is dependent on the adaptability rate of the method.

In order to check the performance of the proposed method in these situations four methods are executed using PETS 2001 test-day (PD) dataset. To achieve this situation, 400<sup>th</sup> frame to 1300<sup>th</sup> frame are utilized. It can be seen in Figure 2 that [8] could not detect the parked vehicle at the centre of the picture as a stable object in the extracted background in the 1300th frame. In addition, there is a newly parked van in the bottom right corner. Except [8], the other methods construct it as a statistic object in the final background. Compared to the others, the more section of van is constructed in the extracted background image by our method.



e) Extracted background by [1].

f) Extracted background by [8].

Figure 2. Detecting entered object being static by the methods using PETS2001 test-day dataset from  $400^{\text{th}}$  frame to  $1300^{\text{th}}$ .

## 4. Conclusions

This paper introduced a new version of LBP, which is an extension of different LBP versions (BGLBP), and designed to handle a greater amount of illumination changes in the background extraction process. The evaluation of BGLBP was done in three different ways. It was evaluated as a block distinguisher in the background extraction process in comparison with the other versions of LBP, and as an independent texture classifier. It was also evaluated as a block distinguisher in the background extraction process in comparison with a number of benchmarks. The results show that not only is the performance of the background extraction process improved using BGLBP but also BGLBP has the potential to be used as a texture descriptor in other applications.

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