An eXtended Center-Symmetric Local Binary Pattern for Background Modeling and Subtraction in Videos

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Abstract: In this paper, we propose an eXtended Center-Symmetric Local Binary Pattern (XCS-LBP) descriptor for background modeling and subtraction in videos. By combining the strengths of the original LBP and the similar CS ones, it appears to be robust to illumination changes and noise, and produces short histograms, too. The experiments conducted on both synthetic and real videos (from the Background Models Challenge) of outdoor urban scenes under various conditions show that the proposed XCS-LBP outperforms its direct competitors for the background subtraction task.

1 INTRODUCTION

The background subtraction (BS) is one of the main steps in many computer vision applications, such as object tracking, behavior understanding and activity recognition (Pietikäinen et al., 2011). The BS process consists basically of: a) background model initialization, b) background model maintenance and c) foreground detection. Many BS methods have been developed during the last few years (Bouwmans, 2014; Sobral and Vacavant, 2014; Shah et al., 2013), and the main resources can be found at the Background Subtraction Web Site[1].

The BS needs to face several challenging situations such as illumination changes, dynamic backgrounds, bad weather, camera jitter, noise and shadows. Several feature extraction methods have been developed to deal with these situations. Color features are the most widely used, but they present several limitations when illumination changes, shadows and camouflage occurrences are present. A variety of local texture descriptors recently have attracted great attention for background modeling, especially the Local Binary Pattern (LBP) because it is simple and fast to compute. Figure 1 (*top*) shows how a (center) pixel is encoded by a series of bits, accordingly to the relative gray levels of its circular neighboring pixels. It shows great invariance to monotonic illumination changes, do not require many parameters to be set, and have a high discriminative power. However, the

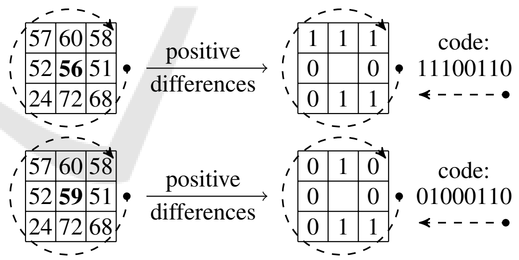

Figure 1: Examples of LBP encoding.

original LBP descriptor in (Ojala et al., 2002) is not efficient for background modeling because of its sensitivity to noise, see Figure 1 (*bottom*) where a little change of the central value greatly affects the resulting code.

The LBP feature of an image consists in building a histogram based on the codes of all the pixels within the image. As it only adopts first-order gradient information between the center pixel and its neighbors, see (Xue et al., 2011), the produced histogram can be rather long. A large number of local texture descriptors based on LBP (Richards and Jia, 2014) have been proposed so far for background modeling. In order to be more robust to noise or illumination changes, most of them are unfortunately either very time-consuming or produce a long feature histogram.

In this paper, we propose to extend the variant by Heikkilä et al. (2009) by introducing a new neighboring pixels comparison strategy that allows the descriptor to be less sensitive to noisy pixels and to produce a short histogram, while preserving robustness to il-

[1] https://sites.google.com/site/backgroundsubtraction/Home

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lumination changes and slightly gaining in time consumption when compared to its direct competitors.

The rest of this paper is organized as follows. Section 2 provides quite an exhaustive overview of LBP-based descriptors. The new descriptor that we propose is described in Section 3. Comparative results obtained on both synthetic and real videos are given in Section 4. Finally, concluding remarks and some perspectives are drawn in Section 5.

2 RELATED WORK

One of the first descriptors based on the LBP for background modeling can be found in (Heikkilä and Pietikäinen, 2006). It improves the original LBP in image areas where the gray values of the neighboring pixels are very close to the center pixel one, *e.g.* sky, grass, etc.

Shimada and Taniguchi (2009) propose a Spatial-Temporal Local Binary Pattern (STLBP) which is robust to short-term illumination changes by using some temporal information. Two variants of LBP, called εLBP and Adaptive εLBP, are developed in (Wang and Pan, 2010; Wang et al., 2010). They are fast to compute and less sensitive to the illumination variation or some color similarity between foreground and background. Heikkilä et al. (2009) propose the Center Symmetric Local Binary Pattern (CS-LBP) descriptor which generates more compact binary patterns by working only with the center-symmetric pairs of pixels. In (Xue et al., 2010), a Spatial Extended Center-Symmetric (SCS-LBP) is presented. It improves the CS-LBP by better capturing the gradient information and hence, making it more discriminative. The authors explain that their SCS-LBP produces a relatively short feature histogram with low computationally complexity. Liao et al. (2010) propose the Scale Invariant Local Ternary Pattern (SILTP) which is more efficient for noisy images. The Center-Symmetric Local Derivative Pattern descriptor (CS-LDP) is described in (Xue et al., 2011). It extracts more detailed local information while preserving the same feature lengths than the CS-LBP, but with a slightly lower precision than the original LBP. Zhou et al. (2011) develop a Spatial-Color Binary Pattern (SCBP) that fuse color and texture information. The SCBP outperforms LBP and SCS-LBP for background subtraction tasks. In (Lee et al., 2011), the authors propose an Opponent Color Local Binary Pattern (OCLBP) that uses color and texture information. The OCLBP extracts several pixel's pieces of information, but the length of the produced histogram makes it useless for some applications. An Uniform LBP Patterns with a new thresholding method can be found in (Yuan et al., 2012). It appears to be tolerant to the interference of the sampling noise. Yin et al. (2013) propose a Stereo LBP on Appearance and Motion (SLBP-AM) which uses information from a set of frames of three different planes. This texture descriptor is not only robust to slight noise, but it also adapts quickly to the large-scale and sudden light changes. A Local Binary Similarity Patterns (LBSP) descriptor is developed in (Bilodeau et al., 2013). Based on absolute absolute differences, it applies on small areas and is calculated inside one image and between two images. This allows LBSP to capture both texture and intensity changes. Noh and Jeon (2012) propose to improve the SILTP (Liao et al., 2010) thanks to a codebook method. The derived descriptor gain in robustness when segmenting moving objects from dynamic and complex backgrounds. Wu et al. (2014) extend SILTP by introducing a novel Center Symmetric Scale Invariant Local Ternary Patterns (CS-SILTP) descriptor which explores spatial and temporal relationships within the neighborhood. The LBP descriptors present a significant drawback as it ignores the intensity information. Because of this, there could be a wrong pixel comparison result when intensity values of pixels differ drastically, but their LBP values are identical. To overcome this drawback, Vishnyakov et al. (2014) propose an intensity LBP (iLBP) to build a fast background model is proposed in (Vishnyakov et al., 2014). It is defined as a collection of LBP descriptor values and intensity values of the image. The main characteristics of all the above reviewed LBP variants, including those we will compare our new descriptor to, are summarized in Table 1.

3 THE XCS-LBP DESCRIPTOR

The original LBP descriptor introduced by Ojala et al. (2002) has proved to be a powerful local image descriptor. It labels the pixels of an image block by thresholding the neighbourhood of each pixel with the center value and considering the result as a binary number. The LBP encodes local primitives such as curved edges, spots, flat areas, etc. In the context of BS, both the current image and the image representing the background model are encoded such that they become a texture-based representation of the scene.

Let a pixel at a certain location, considered as the center pixel $c = (x_c, y_c)$ of a local neighborhood composed of P equally spaced pixels on a circle of radius R. The LBP operator applied to c can be expressed as:

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

Table 1: Comparison of LBP and variants.

Descriptor	Robust to noise	Robust to illumination changes	Uses color information	Uses temporal information	Histogram size with 8 neighbors
Original LBP (Ojala et al., 2002)		●			256
Modified LBP (Heikkilä and Pietikäinen, 2006)	●	●			256
CS-LBP (Heikkilä et al., 2009)		●			16
STLBP (Shimada and Taniguchi, 2009)		●		●	256
εLBP Wang and Pan (2010)		●			256
Adaptive εLBP (Wang et al., 2010)		●			256
SCS-LBP (Xue et al., 2010)	●			●	16
SILTP (Liao et al., 2010)	●				256
CS-LDP (Xue et al., 2011)	●				16
SCBP (Xue et al., 2011)			●		64
OCLBP (Lee et al., 2011)			●		1536
Uniform LBP (Yuan et al., 2012)	●				59
SALBP (Noh and Jeon, 2012)	●				128
SLBP-AM (Yin et al., 2013)	●			●	256
LBSP (Bilodeau et al., 2013)	●	●			256
iLBP (Vishnyakov et al., 2014)		●			256
CS-SILTP (Wu et al., 2014)	●			●	16
XCS-LBP (in this paper)	●	●			16

where g_c is the gray value of the center pixel c and g_i is the gray value of each neighboring pixel, and s is a thresholding function defined as:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

From (1), it is easy to show that the number of binary terms to be summed is $\sum_{i=0}^{P-1} 2^i = 2^P - 1$, so that the length of the resulting histogram (including the bin-0 location) is 2^P. The underlying idea of CS-LBP in (Heikkilä et al., 2009) is to compare the gray levels of pairs of pixels in centered symmetric directions instead of comparing the central pixel to its neighbors. Assuming an even number P of neighboring pixels, the CS-LBP operator is given by:

$$CS-LBP_{P,R}(c) = \sum_{i=0}^{(P/2)-1} s(g_i - g_{i+(P/2)})\, 2^i \quad (3)$$

where g_i and $g_{i+(P/2)}$ are the gray values of center-symmetric pairs of pixels, and s is the thresholding function defined as:

$$s(x) = \begin{cases} 1 & \text{if } x > T \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where T is a user-defined threshold. Since the gray levels are normalized in [0,1], the authors recommend to use of a small value. We will set it to 0.01 in the experiments presented in Section 4. By construction, the length of the histogram resulting from the CS-LBP descriptor falls down to $1 + \sum_{i=0}^{P/2-1} 2^i = 2^{P/2}$. For BS, the CS-LBP encodes the two images to be compared as texture-based images with a lower quantization that slightly favors robustness.

We propose to extend the CS-LBP operator by comparing the gray values of pairs of center-symmetric pixels so that the produced histogram are short as well, but considering the central pixel also. This combination makes the resulting descriptor less sensitive to noise for the BS application. The new LBP variant, called XCS-LBP (eXtended CS-LBP), expresses as:

$$XCS-LBP_{P,R}(c) = \sum_{i=0}^{(P/2)-1} s\left(g_1(i,c) + g_2(i,c)\right) 2^i \quad (5)$$

where the threshold function s, which is used to determine the types of local pattern transition, is defined as a characteristic function:

$$s(x_1 + x_2) = \begin{cases} 1 & \text{if } (x_1 + x_2) \geq 0 \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

and where $g_1(i,c)$ and $g_2(i,c)$ are defined by:

$$\begin{cases} g_1(i,c) = (g_i - g_{i+(P/2)}) + g_c \\ g_2(i,c) = (g_i - g_c)\,(g_{i+(P/2)} - g_c) \end{cases} \quad (7)$$

with the same notation conventions than in equations (1) and (3). It is worth noting that the threshold function does not need a user-defined threshold value, contrary to CS-LBP.

The computation of the original LBP for a neighborhood of size $P = 8$ is illustrated in Figure 2 and the computation of the proposed XCS-LBP is shown

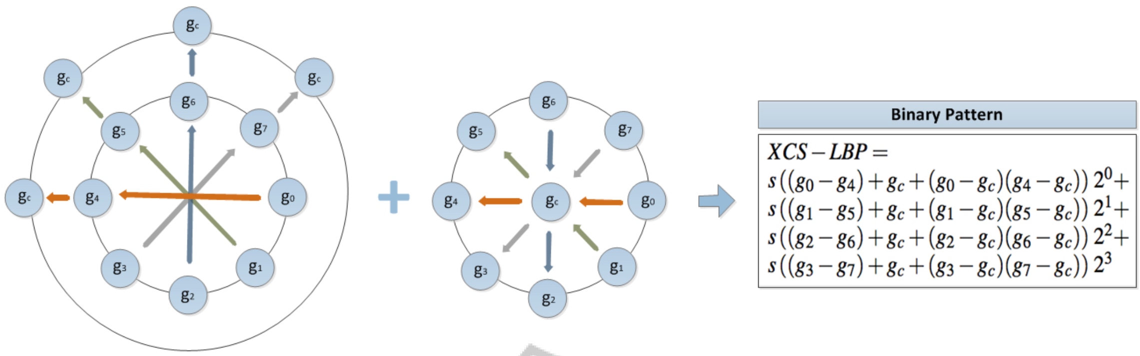

Figure 3: The XCS-LBP descriptor.

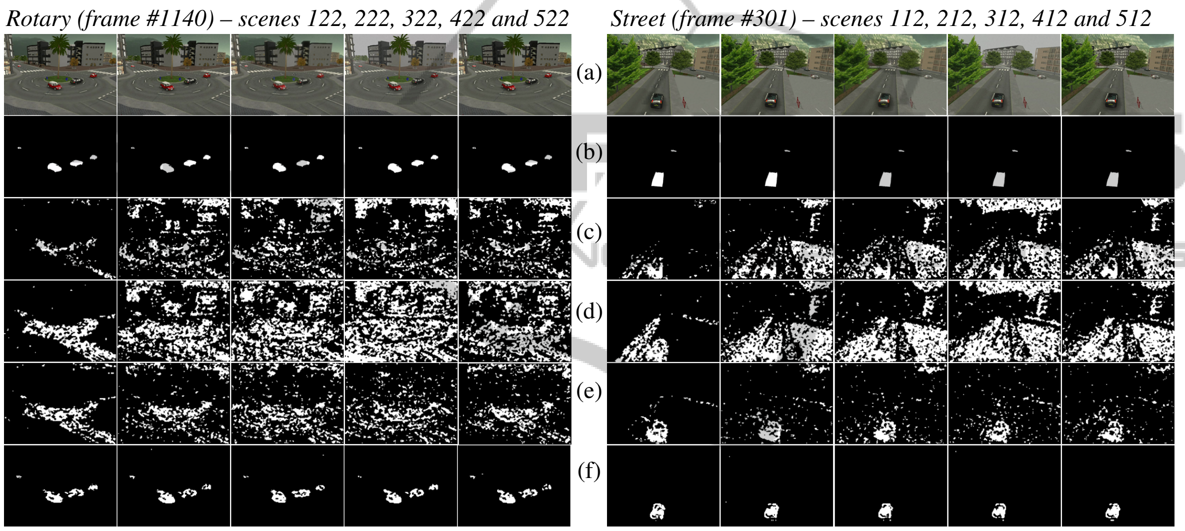

Figure 4: Background subtraction results using the ABL method on synthetic scenes – (a) original frame, (b) ground truth, (c) LBP, (d) CS-LBP, (e) CS-LDP and (f) proposed XCS-LBP.

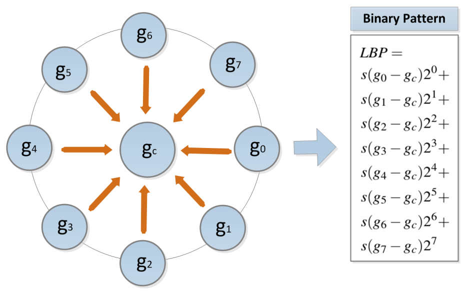

Figure 2: The LBP descriptor.

in Figure 3 in order to make the comparison more understandable for the reader. Note the respective code lengths of 8 and 4 that lead to respective image compressions.

The proposed XCS-LBP produces a shorter histogram than LBP, as short as CS-LBP, but it extracts more image details than CS-LBP because (i) it takes into account the gray value of the central pixel, and (ii) it relies on a new strategy for neighboring pixels comparison. Since it is also more robust to noisy images than both LBP and CS-LBP, the proposed descriptor appears to more efficient for background modeling and subtraction.

4 EXPERIMENTAL RESULTS

Several experiments were conducted to illustrate both the qualitative and quantitative performances of the proposed descriptor XCS-LBP. We use datasets from the BMC (Background Models Challenge) which comprises synthetic and real videos of outdoor situations (urban scenes) acquired with a static camera, under different weather variations such as: wind, sun or rain (Vacavant et al., 2012). We compare XCS-LBP with three other texture descriptors among the reviewed ones, namely:

Table 2: Performance of the different descriptors on synthetic videos of the BMC using the ABL method.

Scenes	Descriptor	Recall	Precision	F-score
Rotary 122	LBP	0.682	0.564	0.618
	CS-LBP	0.832	0.520	0.640
	CS-LDP	0.809	0.523	0.635
	XCS-LBP	**0.850**	**0.784**	**0.816**
Rotary 222	LBP	0.611	0.505	0.553
	CS-LBP	0.673	0.504	0.577
	CS-LDP	0.753	0.510	0.608
	XCS-LBP	**0.852**	**0.782**	**0.815**
Rotary 322	LBP	0.603	0.505	0.550
	CS-LBP	0.647	0.504	0.566
	CS-LDP	0.733	0.507	0.600
	XCS-LBP	**0.829**	**0.793**	**0.810**
Rotary 422	LBP	0.573	0.502	0.535
	CS-LBP	0.609	0.503	0.550
	CS-LDP	0.733	0.508	0.600
	XCS-LBP	**0.751**	**0.780**	**0.765**
Rotary 522	LBP	0.610	0.505	0.553
	CS-LBP	0.663	0.504	0.573
	CS-LDP	0.745	0.509	0.605
	XCS-LBP	**0.852**	**0.732**	**0.787**
Street 112	LBP	0.702	0.530	0.604
	CS-LBP	**0.839**	0.512	0.636
	CS-LDP	0.826	0.525	0.642
	XCS-LBP	0.803	**0.793**	**0.798**
Street 212	LBP	0.636	0.504	0.562
	CS-LBP	0.716	0.503	0.591
	CS-LDP	0.798	0.513	0.624
	XCS-LBP	**0.808**	**0.790**	**0.799**
Street 312	LBP	0.627	0.504	0.558
	CS-LBP	0.699	0.503	0.585
	CS-LDP	**0.801**	0.511	0.624
	XCS-LBP	0.800	**0.796**	**0.798**
Street 412	LBP	0.580	0.501	0.558
	CS-LBP	0.599	0.501	0.546
	CS-LDP	**0.754**	0.507	0.607
	XCS-LBP	0.748	**0.781**	**0.764**
Street 512	LBP	0.628	0.503	0.559
	CS-LBP	0.677	0.503	0.577
	CS-LDP	0.771	0.508	0.612
	XCS-LBP	**0.800**	**0.575**	**0.669**
Average scores	LBP	0.625	0.512	0.565
	CS-LBP	0.695	0.506	0.584
	CS-LDP	0.772	0.512	0.616
	XCS-LBP	**0.809**	**0.761**	**0.782**

Table 3: Performance of the different descriptors on synthetic videos of the BMC using the GMM method.

Scenes	Descriptor	Recall	Precision	F-score
Rotary 122	LBP	0.817	0.701	0.755
	CS-LBP	0.830	0.705	0.763
	CS-LDP	0.819	0.677	0.741
	XCS-LBP	**0.831**	**0.800**	**0.815**
Rotary 222	LBP	0.636	0.653	0.644
	CS-LBP	0.741	0.687	0.713
	CS-LDP	0.651	0.616	0.633
	XCS-LBP	**0.825**	**0.794**	**0.809**
Rotary 322	LBP	0.661	0.646	0.653
	CS-LBP	0.741	0.656	0.696
	CS-LDP	0.674	0.613	0.642
	XCS-LBP	**0.821**	**0.767**	**0.793**
Rotary 422	LBP	0.611	0.585	0.598
	CS-LBP	0.673	0.575	0.620
	CS-LDP	0.611	0.548	0.578
	XCS-LBP	**0.748**	**0.702**	**0.724**
Rotary 522	LBP	0.636	0.627	0.631
	CS-LBP	0.743	0.672	0.706
	CS-LDP	0.605	0.650	0.627
	XCS-LBP	**0.825**	**0.760**	**0.791**
Street 112	LBP	**0.940**	0.674	0.785
	CS-LBP	0.924	0.675	0.780
	CS-LDP	0.938	0.656	0.772
	XCS-LBP	0.844	**0.755**	**0.808**
Street 212	LBP	0.676	0.642	0.659
	CS-LBP	0.752	0.658	0.702
	CS-LDP	0.694	0.577	0.630
	XCS-LBP	**0.833**	**0.760**	**0.795**
Street 312	LBP	0.684	0.633	0.657
	CS-LBP	0.742	0.627	0.680
	CS-LDP	0.729	0.581	0.647
	XCS-LBP	**0.821**	**0.713**	**0.763**
Street 412	LBP	0.619	0.566	0.591
	CS-LBP	0.705	0.567	0.628
	CS-LDP	0.659	0.539	0.593
	XCS-LBP	**0.751**	**0.619**	**0.679**
Street 512	LBP	0.662	0.566	0.610
	CS-LBP	0.727	0.568	0.638
	CS-LDP	0.689	0.551	0.612
	XCS-LBP	**0.828**	**0.629**	**0.715**
Average scores	LBP	0.694	0.629	0.658
	CS-LBP	0.758	0.639	0.693
	CS-LDP	0.707	0.601	0.648
	XCS-LBP	**0.813**	**0.730**	**0.769**

- original LBP (Ojala et al., 2002),
- CS-LBP (Heikkilä et al., 2009) and
- CS-LDP(Xue et al., 2011).

We choose these two last descriptors on fair comparison purpose. Indeed, among those who rely on the same construction principle, *i.e.* *Center Symmetric* (CS), they are the only ones that use neither color nor temporal information, see Table 1. For all descriptors, the neighborhood size is empirically selected so that $P = 8$ and $R = 1$, and we evaluate the performance with two popular background subtraction methods, see (Bouwmans, 2014):

- Adaptive Background Learning (ABL) and
- Gaussian Mixture Models (GMM).

First, we present results of background subtraction on individual frames of five different scenes from two video sequences: *Rotary* (frame #1140) and *Street* (frame #301). Figures 4 and 5 show the foreground detection results using the ABL and the GMM methods, respectively. Our descriptor clearly appears to be less sensitive to the background subtraction method,

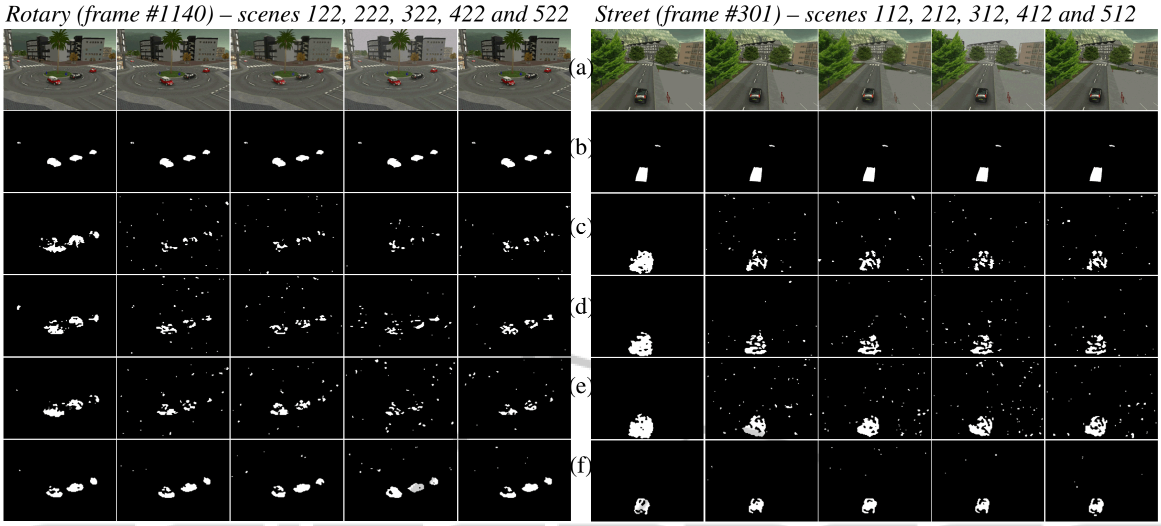

Figure 5: Background subtraction results using the GMM method on synthetic scenes – (a) original frame, (b) ground truth, (c) LBP, (d) CS-LBP, (e) CS-LDP and (f) proposed XCS-LBP.

whereas the three others are very useless in detecting the moving objects when using the ABL method, unless a strong post-processing procedure.

Next, we give quantitative results on the same data. We use three classical measures based on the numbers of true positive TP pixels (correctly detected foreground pixels), false positive FP pixels (background pixels detected as foreground ones), false negative pixels FN (foreground pixels detected as background ones), and true negative pixels (correctly detected background pixels):

- $Recall = \frac{TP}{TP+FN}$,
- $Precision = \frac{TP}{TP+FP}$, and
- $F-score = 2 \times \frac{Recall \times Precision}{Recall + Precision}$.

Tables 2 and 3 shows the scores of the different descriptors obtained on the *Rotary* and *Street* entire scenes when using the ABL and the GMM method, respectively. Best scores are in bold. The proposed XCS-LBP gives the highest value for each score on almost all scenes, except for scene *Street*-[112, 312,412], for which CS-LBP and CS-LDP has achieved the best Recall using ABL, and scene *Street*-112 for which LBP gives the best Recall using GMM.

Note that both CS-LBP and CS-LDP gives lower scores (Precision and F-score) than LBP for some scenes, while our XCS-LBP descriptor takes always the advantage on the others, as shown by the average scores reported at the bottom of each Table.

Finally, we evaluate the proposed descriptor on nine long duration (about one hour) real outdoor video scenes from BMC. Each video sequence shows different challenging situations of real world: moving trees, casted shadows, the presence of a continuous car flow near to the surveillance zone, general climatic conditions (sunny, rainy and snowy conditions), fast light changes and the presence of big objects. The scores obtained using the ABL and the GMM methods are given in Table 4 and 5, respectively. Once again, our descriptor achieved the best scores on almost always scenes, even when using the simple ABL method whereas it dramatically compromises the other descriptors. The average scores reported at the bottom of each Table show that our XCS-LBP outperforms the original LBP and both the similar construction-based CS-LBP and CS-LDP descriptors, the latter one being less performant than the LBP using GMM method. We use Matlab R2013a on a MacBook Pro (OS X 10.9.4) equipped with 2.2 GHz Intel Core i7 and 8 GB - 1333 MHz DDR3.

We collected the elapsed CPU times needed to segment the foregrounds using the ABL and the GMM methods, averaged over the nine real videos of BMC. Since the reference is the (fastest) LBP descriptor, the times are divided by LBP ones. Table 6 reports the resulting ratios for the compared CS descriptors. Our XCS-LBP shows slightly better time performance than both CS-LBP and CS-LDP.

5 CONCLUSION

In this paper, a new texture descriptor for background modeling is proposed. It combines the strengths

Table 4: Performance of the different descriptors on real-world videos of the BMC using the ABL method.

Videos	Descriptor	Recall	Precision	F-score
Boring parking, active bkbg	LBP	0.555	0.512	0.533
	CS-LBP	0.663	0.539	0.595
	CS-LDP	**0.712**	0.556	0.624
	XCS-LBP	0.673	**0.628**	**0.650**
Big trucks	LBP	0.456	0.490	0.473
	CS-LBP	0.664	0.583	0.621
	CS-LDP	**0.675**	0.673	0.674
	XCS-LBP	0.623	**0.788**	**0.696**
Wandering students	LBP	0.500	0.500	0.500
	CS-LBP	0.632	0.525	0.573
	CS-LDP	0.691	0.566	0.622
	XCS-LBP	**0.854**	**0.714**	**0.778**
Rabbit in the night	LBP	0.562	0.515	0.537
	CS-LBP	0.657	0.515	0.577
	CS-LDP	0.742	0.561	0.639
	XCS-LBP	**0.818**	**0.706**	**0.758**
Snowy christmas	LBP	0.568	0.516	0.541
	CS-LBP	0.640	0.508	0.567
	CS-LDP	0.684	0.513	0.586
	XCS-LBP	**0.719**	**0.557**	**0.628**
Beware of the trains	LBP	0.542	0.511	0.526
	CS-LBP	0.608	0.556	0.581
	CS-LDP	0.711	0.618	0.662
	XCS-LBP	**0.780**	**0.674**	**0.723**
Train in the tunnel	LBP	0.524	0.505	0.514
	CS-LBP	0.636	0.640	0.638
	CS-LDP	**0.668**	0.659	0.663
	XCS-LBP	0.655	**0.688**	**0.672**
Traffic during windy day	LBP	0.491	0.497	0.494
	CS-LBP	0.597	0.528	**0.560**
	CS-LDP	**0.589**	0.515	0.550
	XCS-LBP	0.572	**0.529**	0.550
One rainy hour	LBP	0.536	0.508	0.521
	CS-LBP	0.563	0.504	0.532
	CS-LDP	0.658	0.520	0.581
	XCS-LBP	**0.694**	**0.649**	**0.671**
Average scores	LBP	0.526	0.506	0.515
	CS-LBP	0.629	0.544	0.583
	CS-LDP	0.681	0.576	0.558
	XCS-LBP	**0.710**	**0.659**	**0.681**

of the original Local Binary Pattern (LBP) and the Center-Symmetric (CS) LBPs. Thus, the new variant XCS-LBP (eXtended CS-LBP) produces a shorter histogram than LBP, by its CS-construction. It is also tolerant to illumination changes as LBP and CS-LBP are whereas CS-LDP is not, and robust to noise as CS-LDP is whereas LBP and CS-LBP are not. We compared the XCS-LBP to the original LBP and to its two direct competitors on both synthetic and real videos of the Background Modeling Challenge (BMC) using two popular background subtraction methods. The experimental results show that the proposed descriptor qualitatively and quantitatively outperforms the mentioned descriptors, making it a serious candidate for the background substation task in computer vision applications.

Table 5: Performance of the different descriptors on real-world videos of the BMC using the GMM method.

Videos	Descriptor	Recall	Precision	F-score
Boring parking, active bkbg	LBP	0.684	0.587	0.632
	CS-LBP	**0.716**	0.593	**0.649**
	CS-LDP	0.674	0.579	0/623
	XCS-LBP	0.680	**0.607**	0.641
Big trucks	LBP	0.695	0.778	**0.734**
	CS-LBP	**0.698**	0.773	0.733
	CS-LDP	0.649	0.758	0.699
	XCS-LBP	0.630	**0.792**	0.702
Wandering students	LBP	0.704	0.667	0.685
	CS-LBP	0.700	0.640	0.668
	CS-LDP	0.654	0.634	0.643
	XCS-LBP	**0.826**	**0.742**	**0.782**
Rabbit in the night	LBP	0.767	0.659	0.709
	CS-LBP	**0.826**	0.626	0.712
	CS-LDP	0.706	0.619	0.659
	XCS-LBP	0.805	**0.684**	**0.740**
Snowy christmas	LBP	**0.750**	0.519	0.614
	CS-LBP	0.734	0.516	0.606
	CS-LDP	0.625	0.510	0.562
	XCS-LBP	0.726	**0.538**	**0.618**
Beware of the trains	LBP	0.657	0.685	0.671
	CS-LBP	0.699	0.664	0.681
	CS-LDP	0.641	0.642	0.642
	XCS-LBP	**0.759**	**0.731**	**0.744**
Train in the tunnel	LBP	**0.724**	**0.711**	**0.717**
	CS-LBP	0.710	0.675	0.692
	CS-LDP	0.679	0.697	0.688
	XCS-LBP	0.695	0.680	0.687
Traffic during windy day	LBP	0.523	0.509	0.516
	CS-LBP	**0.553**	**0.520**	**0.536**
	CS-LDP	0.527	0.510	0.518
	XCS-LBP	0.532	0.518	0.525
One rainy hour	LBP	**0.867**	0.574	**0.691**
	CS-LBP	0.774	0.589	0.669
	CS-LDP	0.797	0.556	0.655
	XCS-LBP	0.761	**0.628**	0.688
Average scores	LBP	0.708	0.632	0.663
	CS-LBP	0.712	0.622	0.661
	CS-LDP	0.661	0.612	0.632
	XCS-LBP	**0.713**	**0.658**	**0.681**

Table 6: Elapsed CPU times (averaged on the nine real-world videos of the BMC) over LBP times.

Descriptor	CS-LBP	CS-LDP	XCS-LBP
ABL	1.10	1.12	1.09
GMM	1.06	1.07	1.05

Future works will explore how to extend the proposed descriptor to include temporal relationships between neighboring pixels for dynamic texture classification or human action recognition.

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