

DYNAMIC BACKGROUND SUBTRACTION BASED ON SPATIAL EXTENDED CENTER-SYMMETRIC LOCAL BINARY PATTERN

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Introduction

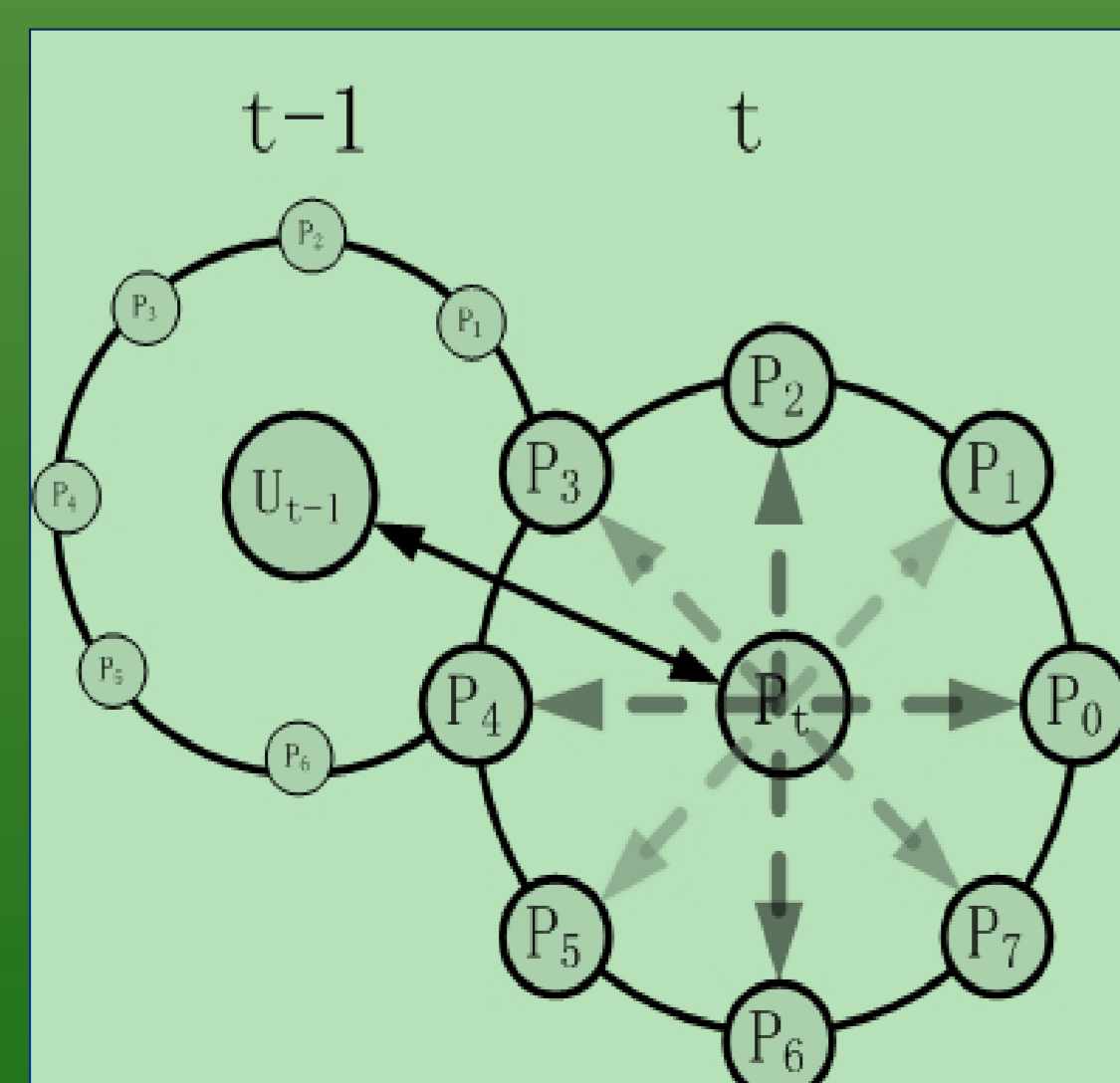
We focus on the moving objects detection in dynamic scenes. We first extend the center-symmetric local binary pattern (CS-LBP) operator into the temporal domain and propose a new operator named spatial extend center-symmetric local binary pattern (SCS-LBP). Then combining this operator with an improved temporal distribution estimation scheme, we propose a novel background subtraction approach where each pixel is modeled by a group of adaptive SCS-LBP histograms and updated by a scheme. Our method is robust to dynamic background and has low computational cost compared to the local binary pattern (LBP) based method. Experiments on two challenging sequences demonstrate its effectiveness.

Methods

◆ SCS-LBP operator

$$SCS-LBP_{R,N}(x,y,t) = \sum_{i=0}^{(N/2)-1} s(p_{(i,t)} - p_{(i+(N/2),t)})2^i + f(p_{(x,y,t)} - \bar{\mu}_{(x,y,t-1)})2^{N/2} \quad (1)$$

LBP and CS-LBP only consider the spatial information. We extend the CS-LBP and propose our new operator SCS-LBP, which extracts both the spatial and temporal motion information at the same time.



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

$$f(t) = \begin{cases} 0 & \text{if } |p_{(x,y,t)} - \bar{\mu}_{(x,y,t-1)}| < 2.5 * \bar{\sigma}_{(x,y,t-1)} \\ 1 & otherwise \end{cases} \quad (3)$$

$P_{(i,t)}, P_{(i+(N/2),t)}$: grey level of center-symmetric pairs of pixels in the current frame. $f(t)$: temporal relationship function. R and N are the radius and pixel numbers.

◆ Background Modeling Method

Feature Selection: The SCS-LBP histogram is selected as the modeling feature which is computed over a circular region of radius R_{region} around the pixel. Each pixel consists of adaptive SCS-LBP histograms.

Similarity Measure: histogram intersection

$$\bigcap(m,h) = \sum_{i=0}^L (m(i), h(i)) \quad (4)$$

m, h : existing and current histograms. L is the number of histogram bins. i is the index.

Updating Method:

$$\bar{u}_t = (1 - \beta)\bar{u}_{t-1} + \beta I_t \quad (5)$$

$$\bar{\sigma}_t^2 = (1 - \beta)\bar{\sigma}_{t-1}^2 + \frac{\beta}{2}(I_t - I_{t-1})^2 \quad (6)$$

$$m_k = (1 - \alpha)m_k + \alpha h \quad (7)$$

$$\omega_k = (1 - \alpha)\omega_k + \alpha M_k \quad (8)$$

$(0 < \alpha, \beta < 1)$: learning rate

M_k : 1 for the matching histogram and 0 for others

ω : histogram weight

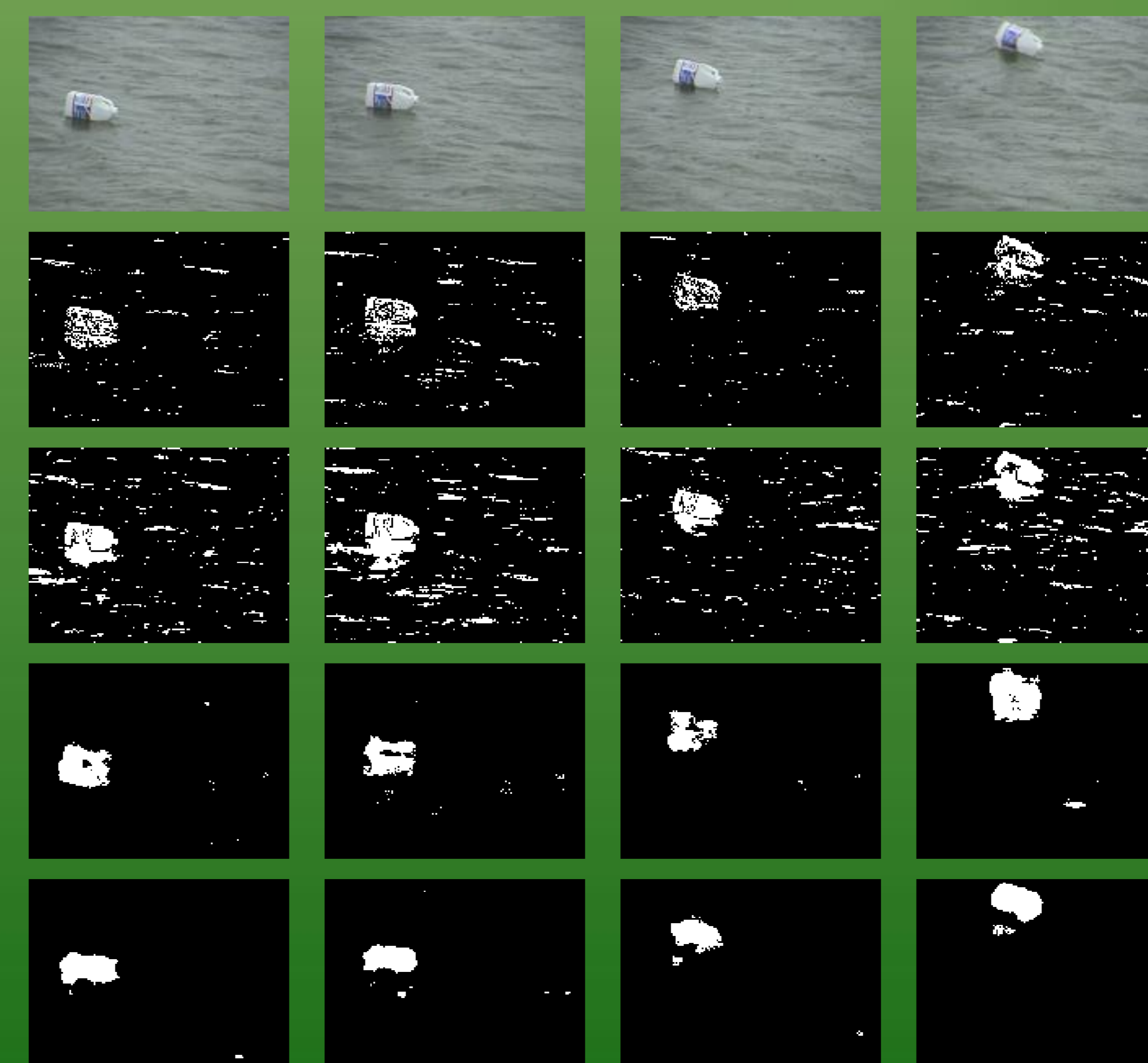
Results



Frame: 247th, 249th, 252th, 256th

Row Num: 1st: Original frame; 2nd: GMM; 3rd: KDE; 4th: LBP; 5th: Our method(SCS-LBP)

Rippling Water



Frame: 182th, 186th, 202th, 216th

Waving Trees

Method	GMM	KDE	LBP	SCS-LBP	
DR (%)	247 th	69.69	77.58	93.94	93.84
	249 th	65.23	79.08	93.64	95.37
	252 th	66.16	79.14	95.16	96.70
	256 th	63.58	69.40	87.47	91.69
FAR (%)	247 th	25.39	33.71	9.35	13.10
	249 th	26.49	33.25	8.40	11.23
	252 th	23.98	33.42	11.22	12.99
	256 th	30.04	40.54	6.51	8.62

Rippling Water

Method	GMM	KDE	LBP	SCS-LBP	
DR (%)	182 th	55.96	83.03	54.34	92.32
	186 th	56.63	81.93	47.39	86.14
	202 th	49.12	80.62	49.34	80.18
	216 th	57.69	74.70	84.21	91.70
FAR (%)	182 th	63.21	71.54	57.17	16.61
	186 th	67.55	77.83	56.38	10.25
	202 th	50.77	66.51	49.55	20.35
	216 th	66.27	74.15	48.51	17.93

(DR: Detection Rate FAR: False Alarm Rate)

Speed Comparison

Method	Average running time per frame(second)	
	Waving Trees	Rippling Water
LBP	7.28	7.32
SCS-LBP	5.90	5.78
Time Reduction	18.96%	21.04%

Conclusion

The SCS-LBP based background subtraction is more robust to dynamic scenes and our method also has low computational complexity compared to the LBP method.

Main References

- [1].Marko Heikkila et al., "Description of interest regions with local binary patterns," Pattern Recognition,2009.
- [2].Pedro Gil-JimG é nez et al., "Continuous variance estimation in video surveillance sequences with high illumination changes," Signal Processing, 2009.