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

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Introduction

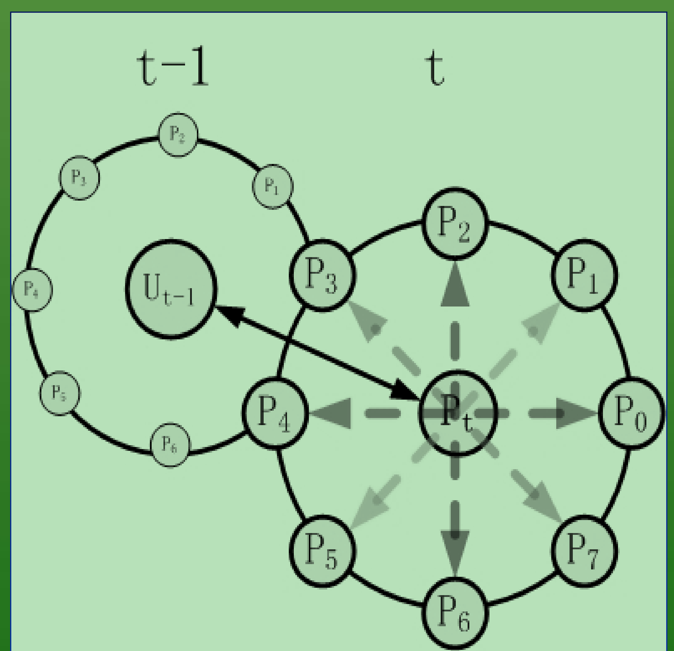
We focus on the moving objects detection in dynamic scenes. We first extend the center-symmetric local binary pattern (CS-LBP) operator into the temporal domain and propose a new operator named spatial extend center-symmetric local binary pattern (SCS-LBP). Then combining this operator with an improved 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.



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

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

$p_{(i,t)}, p_{(i+(N/2),t)}$: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:

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

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

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

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

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

M_k :1 for the matching histogram and 0 for others

ω : histogram weight

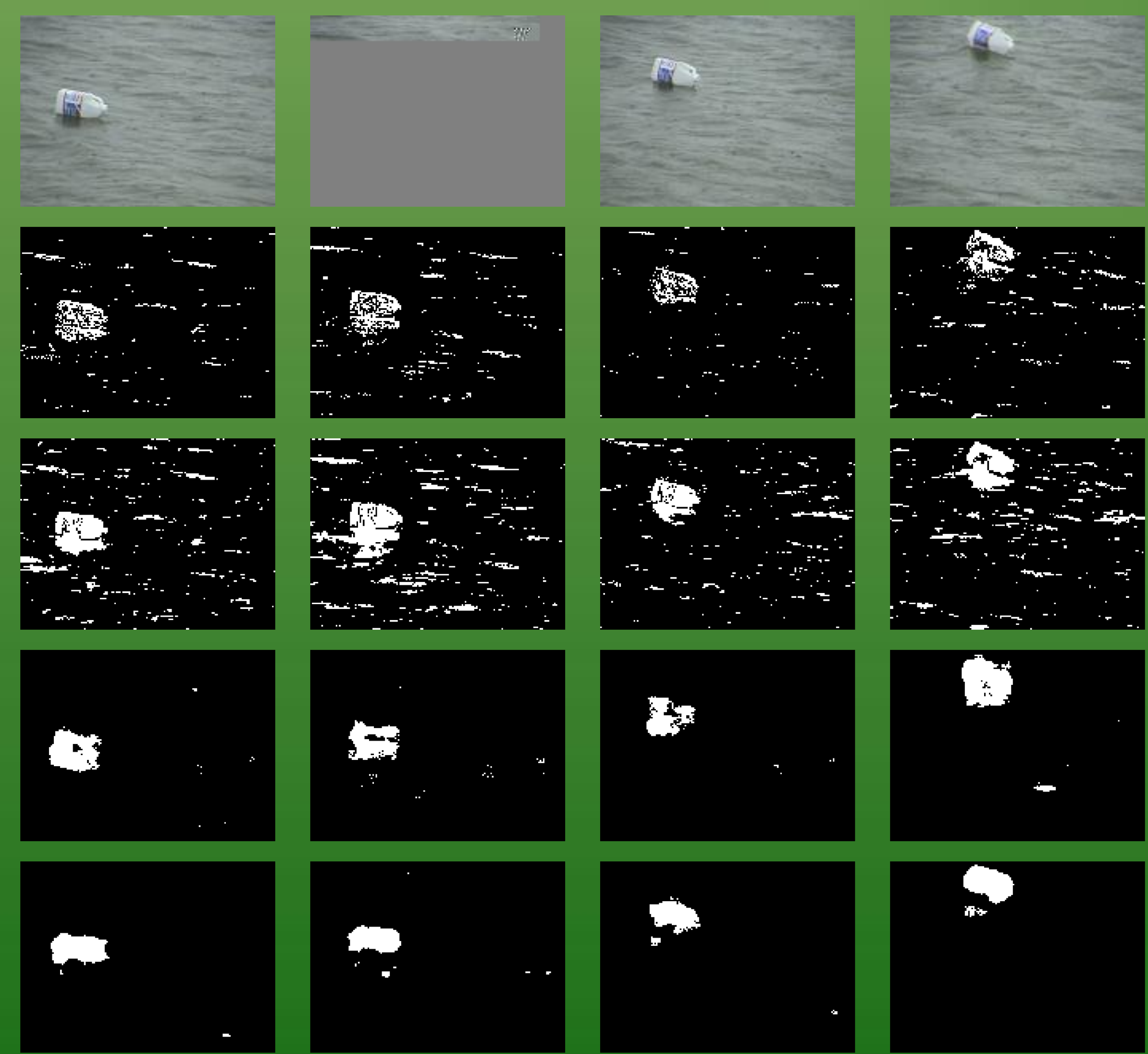
Results

Waving Trees

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

Rippling Water

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