REAL-TIME SEMANTIC BACKGROUND SUBTRACTION

Anthony Cioppa Marc Braham Marc Van Droogenbroeck

Department of Electrical Engineering and Computer Science (Montefiore Institute), University of Liège, Belgium

Special Session on "Dynamic Background Reconstruction / Subtraction for Challenging Environments"

Real-time semantic background subtraction

For a more dynamic presentation of this work, please check our ▷ YouTube video! bit.ly/RT-SBS



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Background subtraction in video sequences



Principle of BGS algorithms

Background model to store background features

Distance function to compare the current frame with the background model

Update strategy to update the background model

Principle of BGS algorithms



Current frame





Background model



Threshold

Typical challenges and traditional solutions

Typical challenges

Color camouflage

Light changes

Dynamic backgrounds

Shadows

. . .

Traditional solutions

Complex background modeling strategies (GMM, KDE, Codebook, ViBe, ...)

Sophisticated hand-crafted features (LBP, LBSP, HRI, ...)

More recently : deep learning

Semantic background subtraction (SBS)



6	Decision table of SBS			
	Classifiers		Output	
	$B_t(x,y)$	$S_t(x,y)$	$D_t(x,y)$	
(L1)	BG	"?"	BG	
(L2)	BG	BG	BG	
(L3)	BG	FG	FG	
(L4)	FG	"?"	FG	
(L5)	FG	BG	BG	
(L6)	FG	FG	FG	

State-of-the-art classification performance **for unsupervised BGS** on the CDNet 2014 dataset.

Braham et al., Semantic background subtraction, ICIP 2017.

Time diagram of SBS



SBS requires a semantic segmentation map for each frame

But...

The best semantic segmentation networks

are not real-time

Lower performances are obtained with

the fastest semantic segmentation networks

How can we obtain high-quality segmentation maps for BGS in real-time?

Real-time semantic background subtraction (RT-SBS)



Decision table of RT-SBS

Key idea for missing semantics:

Reuse previous semantic decision

if pixel color hasn't changed too much!

	Decision table of RT-SBS			
	Classifiers		Output	
	$B_t(x,y)$	$S_{t^*}(x,y)$	$C_t(x,y)$	$D_t(x,y)$
(L1)	BG	"?"	" × "	BG
(L2)	BG	BG	" x "	BG
(L3)	BG	FG	No Change	FG
(L4)	BG	FG	Change	BG
(L5)	FG	"?"	" × "	FG
(L6)	FG	BG	No Change	BG
(L7)	FG	BG	Change	FG
(L8)	FG	FG	" x "	FG

Decision table of RT-SBS

The pixel color change at time t, $C_t(x,y)$, is computed by a threshold on the Manhattan distance between the pixel current color value and its **previous** color value when semantic information was last available.

	Decision table of RT-SBS			
	Classifiers			Output
	$B_t(x,y)$	$S_{t^*}(x,y)$	$C_t(x,y)$	$D_t(x,y)$
(L1)	BG	"?"	" × "	BG
(L2)	BG	BG	" * "	BG
(L3)	BG	FG	No Change	FG
(L4)	BG	FG	Change	BG
(L5)	FG	"?"	" x "	FG
(L6)	FG	BG	No Change	BG
(L7)	FG	BG	Change	FG
(L8)	FG	FG	" × "	FG

Decision table of RT-SBS

Foreground and background have different color dynamics.

Hence, the threshold used to compute $C_t(x,y)$ depends on $S_t(x,y)$.

	Decision table of RT-SBS			
	Classifiers			Output
	$B_t(x,y)$	$S_{t^*}(x,y)$	$C_t(x,y)$	$D_t(x,y)$
(L1)	BG	"?"	" × "	BG
(L2)	BG	BG	" * "	BG
(L3)	BG	FG	No Change	FG
(L4)	BG	FG	Change	BG
(L5)	FG	"?"	" × "	FG
(L6)	FG	BG	No Change	BG
(L7)	FG	BG	Change	FG
(L8)	FG	FG	" × "	FG

Improving the BGS algorithm with a feedback loop

We use ViBe as BGS algorithm as it is the best real-time one.

We add a **feedback loop** to upgrade ViBe's decisions.

D_t replaces *B_t* as updating mask for the background model.



Time Diagram of RT-SBS



Performance of RT-SBS (built upon ViBe)

Evaluation on the CDNet 2014 dataset

PSPNet used as semantic segmentation algorithm (~ 5 fps)

Parameters of RT-SBS optimized to maximize the overall F_1 -score for each semantic frame rate X.



Comparison with unsupervised BGS algorithms

Unsupervised BGS algorithms	F_1	fps
SemanticBGS (SBS with IUTIS-5) [14]	0.789	pprox 7
IUTIS-5 [9]	0.772	≈ 10
IUTIS-3 [9]	0.755	≈ 10
WisenetMD [20]	0.754	≈ 12
WeSamBE [21]	0.745	≈ 2
PAWCS [22]	0.740	$\approx 1-2$
ViBe [7]	0.619	≈ 152
RT-SBS at $X:5$	0.746	25
RT-SBS at $X : 10$	0.734	50
RT-SBS at $X:5$	0.828	25
and scene-specific optimization	0.020	25

Qualitative results



Conclusion

RT-SBS extends the semantic background subtraction (SBS) algorithm for real-time applications.

RT-SBS uses high-quality semantic information which can be provided at any pace and independently for each pixel and checks its relevance through time using a change detection algorithm.

RT-SBS outperforms real-time background subtraction algorithms and competes with the non-real-time state-of-the-art ones.





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Code in Python for all of our works with easy install procedures on docker. You can reproduce our exact results!



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