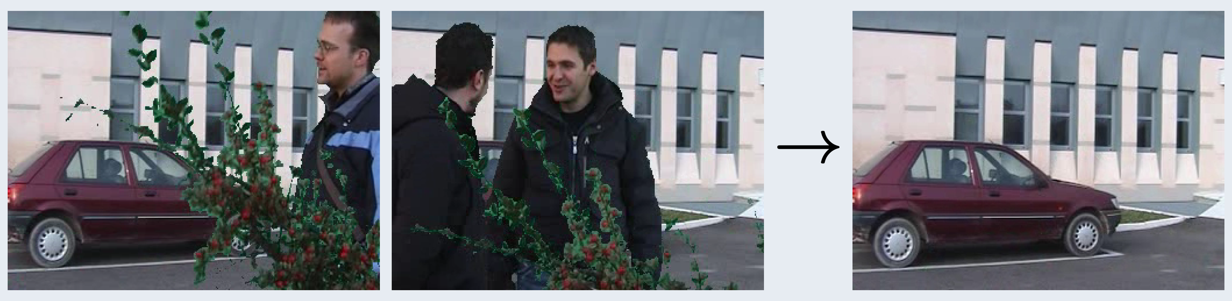
Is a Memoryless Motion Detection Truly Relevant for Background Generation with LaBGen?

Benjamin Laugraud and Marc Van Droogenbroeck
{blaugraud, m.vandroogenbroeck}@ulg.ac.be
Montefiore Institute, University of Liège, Belgium

Link to the article

1. Introduction

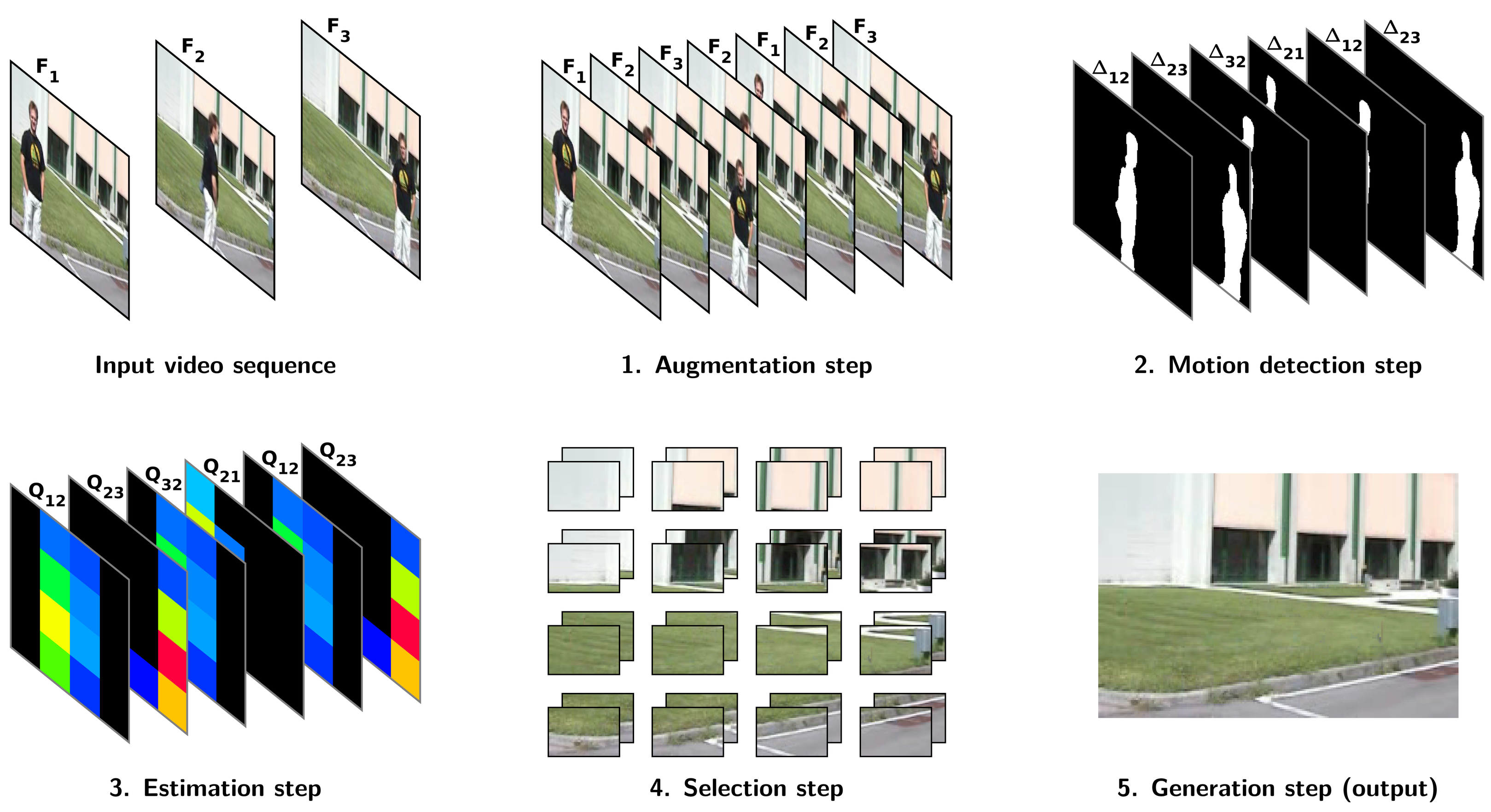
Given a video sequence acquired from a fixed viewpoint, the stationary background generation problem consists in generating a unique image representing the background.



- The LaBGen background generation method combines a pixel-wise median filter and a patch selection mechanism based on a motion detection performed by a background subtraction (BGS) algorithm.
- Surprisingly, the frame difference algorithm provides the most effective motion detection on average. Compared to other BGS algorithms, it detects motion between two frames without relying on additional past frames, and is therefore *memoryless*.
- In this work, we experimentally check whether the memoryless property is truly relevant for LaBGen, and whether the effective motion detection provided by the frame difference is not an isolated case.
- For this purpose, we introduce LaBGen-OF, a variant of LaBGen leverages memoryless dense optical flow (OF) algorithms for motion detection.

2. The LaBGen Background Generation Framework

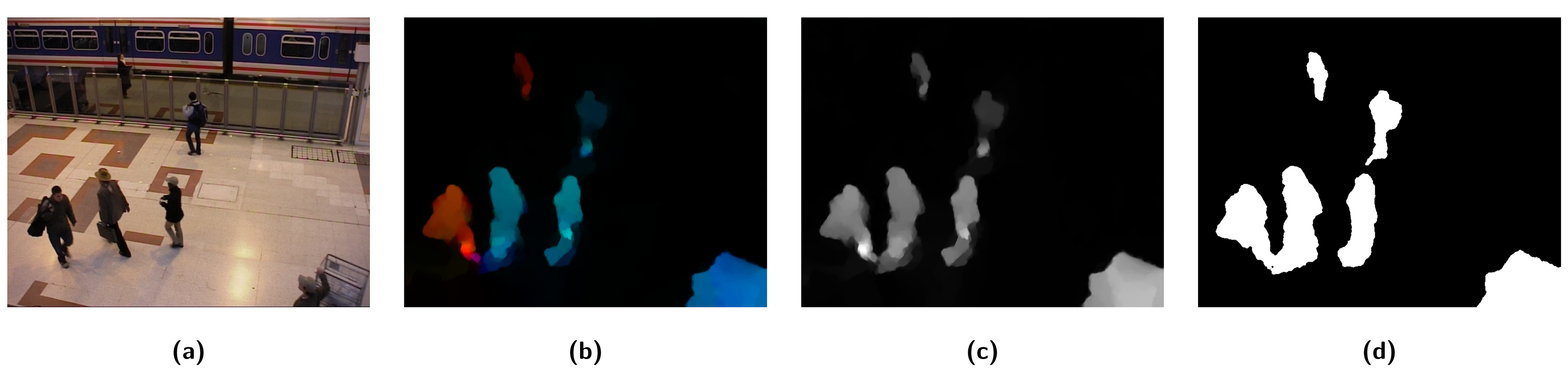
1. An *augmentation step* increases the length of the input video sequence according to a parameter $\mathcal{P}$. This is performed by duplicating the frames of the sequence in the forwards and backwards chronological orders alternatively.
2. For each frame of the augmented sequence, a *motion detection step* determines which pixels belong to the background using a BGS algorithm $\mathcal{A}$. The classification results are put in a binary *segmentation map*.
3. To estimate *quantities of motion* spatially, an *estimation step* divides the image plane into $\mathcal{N} \times \mathcal{N}$ spatial areas. Then, for each patch, quantities of motion are estimated by counting the number of pixels classified as foreground.
4. For each spatial area, a *selection step* builds a subset of $\mathcal{S}$ patches. The elements belonging to this subset are the $\mathcal{S}$ patches associated to the smallest quantities.
5. Finally, a *generation step* builds the background image by applying a pixel-wise median filter on each subset built during the previous step.



The figure above illustrates the different steps of LaBGen applied on a video sequence composed of three frames with $\mathcal{P} = 3$, $\mathcal{N} = 4$, $\mathcal{S} = 2$, and $\mathcal{A} = \text{Ground-truth}$.

3. LaBGen-OF: A Variant Incorporating Optical Flow

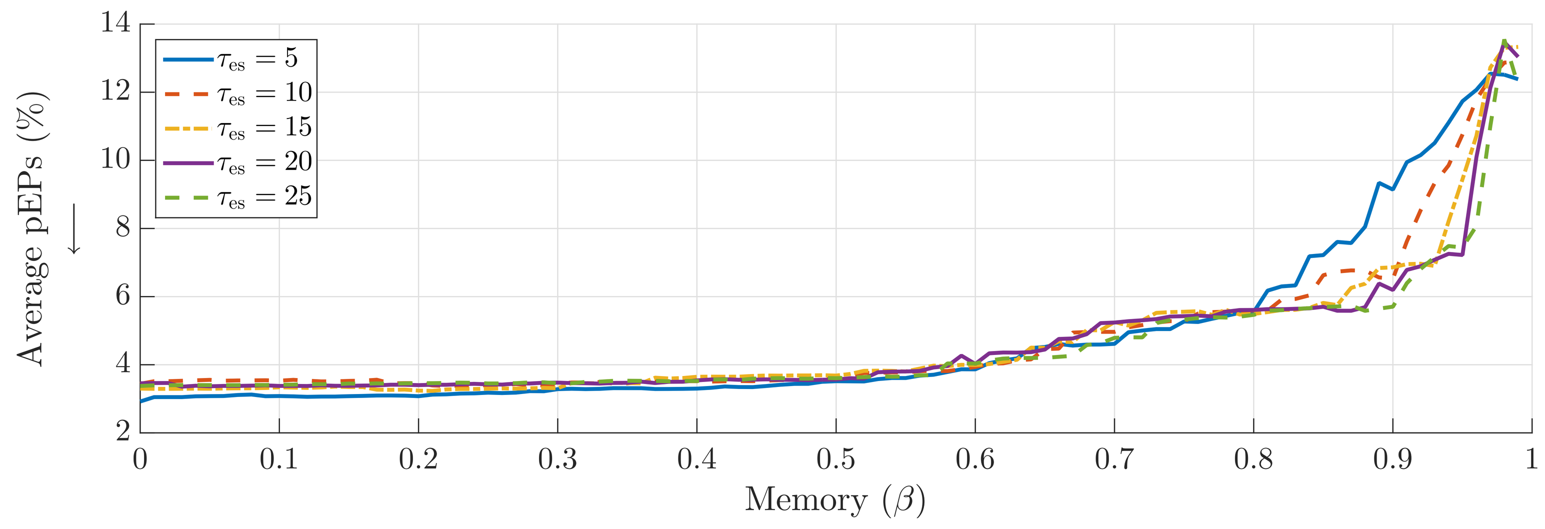
For incorporating an OF algorithm in the motion detection step of LaBGen-OF, we transform its output into a binary segmentation map as follows:



the application of a dense OF algorithm on the frame (a) and its successor produces a vector field such as (b) (the hue and saturation components represent the angle and magnitude, respectively). Then, the spatially normalized ℓ^2-norms are computed (c), and thresholded according to a parameter τ (d), in order to get a binary segmentation map.

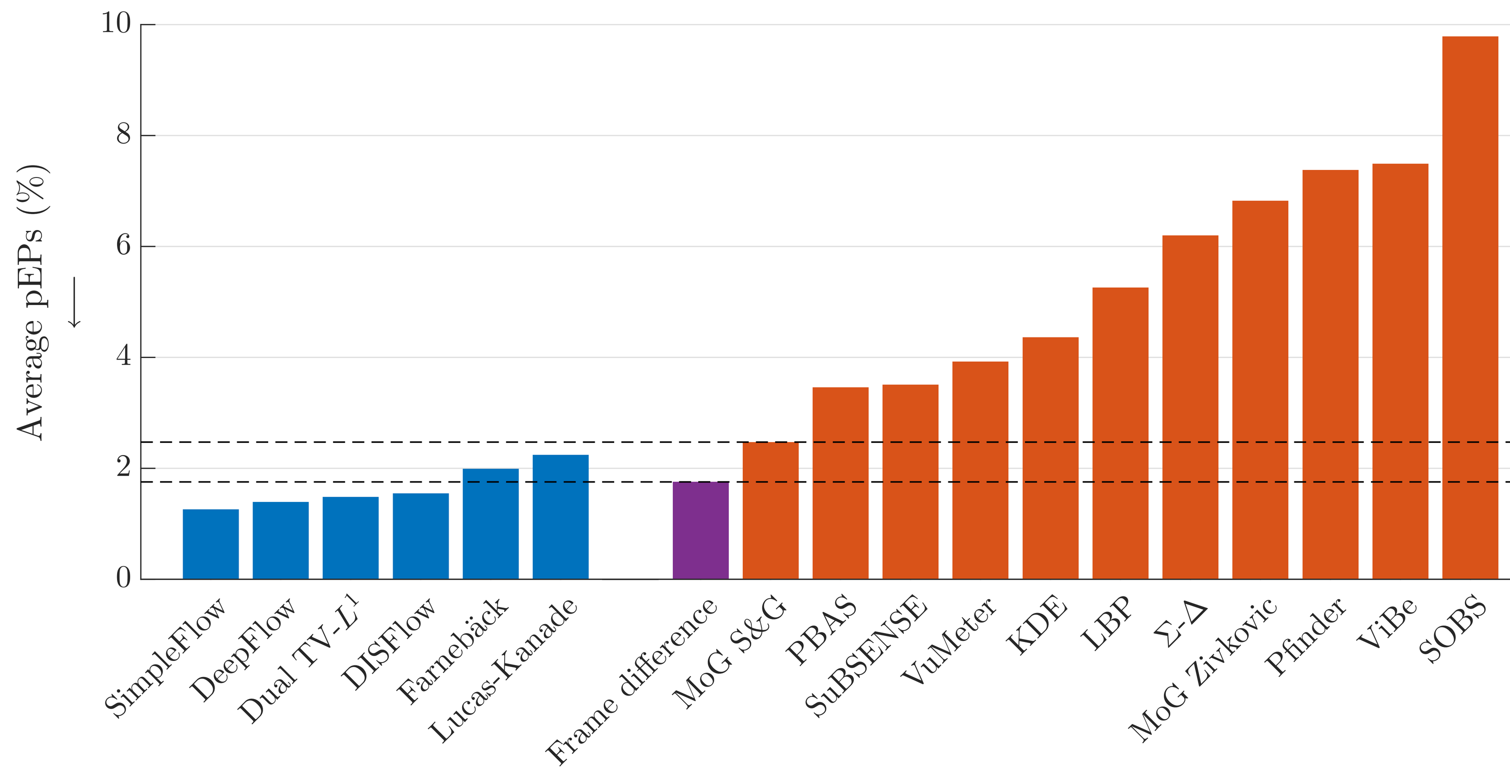
4. Impact of the Motion Detection Memory on the Performance

Our first experiment consists in modeling the amount of memory being used by the motion detection component to measure its impact on the performance of LaBGen. For that purpose, we use an exponential smoothing based BGS algorithm as a motion detector in LaBGen. Its parameter β allows us to tune the amount of memory being used. One can observe that the performance of LaBGen decreases as long as the amount of memory increases.



5. Comparison of Motion Detectors With or Without Memory

In this experiment, we compare on the SBI dataset the average performance achieved by LaBGen embedded with the memoryless frame difference ■ and other BGS algorithms with memory ■, and LaBGen-OF with memoryless OF algorithms ■. One can observe that the average performance achieved by LaBGen-OF embedded with any OF algorithm is always better than the one with any BGS algorithm with memory.



6. Average Performance of LaBGen-OF on SBMnet

In this experiment, we finely optimize the parameters of LaBGen-OF on a larger set of video sequences composed of the SBI dataset, and the sequences of the SBMnet dataset provided with ground-truth. This optimization has been carried out with respect to each OF algorithm. One can observe that most OF algorithms are adequate memoryless substitutes for the frame difference algorithm in our background generation framework. However, the use of a good OF algorithm slows down the computational performance.

	Best parameters				Averaged metrics						Run time
$\mathcal{A}$	$\mathcal{P}$	$\mathcal{N}$	$\mathcal{S}$	τ	AGE ↓	pEPs ↓	pCEPs ↓	MS-SSIM ↑	PSNR ↑	CQM ↑	(fps) ↑
DeepFlow	3	8	119	0.04	4.0621	2.60%	1.20%	0.9708	33.1041	33.7400	5
Lucas-Kanade	1	6	63	0.03	4.2515	3.02%	1.60%	0.9718	32.8775	33.5150	44
DISFlow	1	3	57	0.02	4.7678	3.91%	2.15%	0.9520	32.3675	32.9819	124
Farnebäck	3	3	83	0.05	4.5974	3.42%	1.70%	0.9521	32.2720	32.8954	13
SimpleFlow	3	6	49	0.06	4.4212	2.94%	1.36%	0.9596	31.9124	32.5169	5
Dual TV-L^1	5	10	75	0.06	4.3821	2.90%	1.41%	0.9669	31.8324	32.4793	2
LaBGen + Frame difference					4.5863	3.31%	1.63%	0.9464	31.8394	32.4585	1312

7. Comparison to Other Background Generation Methods

Here is the Top-8 reported on the SBMnet web platform the March 8th, 2017 in which the performance achieved by LaBGen-OF has been inserted (in blue). According to the average ranking across categories reported in the table below, LaBGen-OF is now ranked first.

Method	Average ranking ↓	A. r. across categories ↓	Average AGE ↓	Average pEPs ↓	Average pCEPs ↓	Average MS-SSIM ↑	Average PSNR ↑	Average CQM ↑	Run time (fps) ↑
MSCL (anon.)	**1.17**	4.75	**5.9545**	**5.24%**	**1.71%**	0.9410	**30.8952**	**31.7049**	unknown
LaBGen-OF	2.00	**4.25**	6.1897	5.66%	2.32%	**0.9412**	29.8957	30.7006	5
BEWiS	4.17	5.63	6.7094	5.92%	2.66%	0.9282	28.7728	29.6342	3
LaBGen	4.67	7.25	6.7090	6.31%	2.65%	0.9266	28.6396	29.4668	1312
LaBGen-P	5.83	8.00	7.0738	7.06%	3.19%	0.9278	28.4660	29.3196	126
Photomontage	6.33	10.38	7.1950	6.86%	2.57%	0.9189	28.0113	28.8719	unknown
SC-SOBS-C4	7.33	8.88	7.5183	7.11%	2.42%	0.9160	27.6533	28.5601	unknown
MAGRPCA	8.67	8.88	8.3132	9.94%	5.67%	0.9401	28.4556	29.3152	2.5
Temporal median	10.33	8.25	8.2731	9.84%	5.46%	0.9130	27.5364	28.4434	100

8. Conclusion

A memoryless motion detection helps reaching the best achievable average performances in our background generation framework. Moreover, using LaBGen-OF, we also learned that a memoryless motion detection algorithm enables to achieve a better performance than several popular BGS algorithms with memory. Finally, LaBGen-OF outperforms LaBGen embedded with the frame difference and almost all state-of-the-art background generation methods on the SBMnet dataset.

Advanced Concepts for Intelligent Vision Systems (ACIVS) — Antwerp, Belgium — September 19th 2017