Time Ordering Shuffling for Improving Background Subtraction

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Link to the article

1. Introduction

In the context of background subtraction, we take for granted that the chronological/forwards time order is the most appropriate for dealing with videos. However, this has never been extensively checked. Thus, our goal is to question, in a prospective view, the impact of changing the time ordering of frames for the segmentation and updating phases. The flowchart of our method is given in Figure 1.

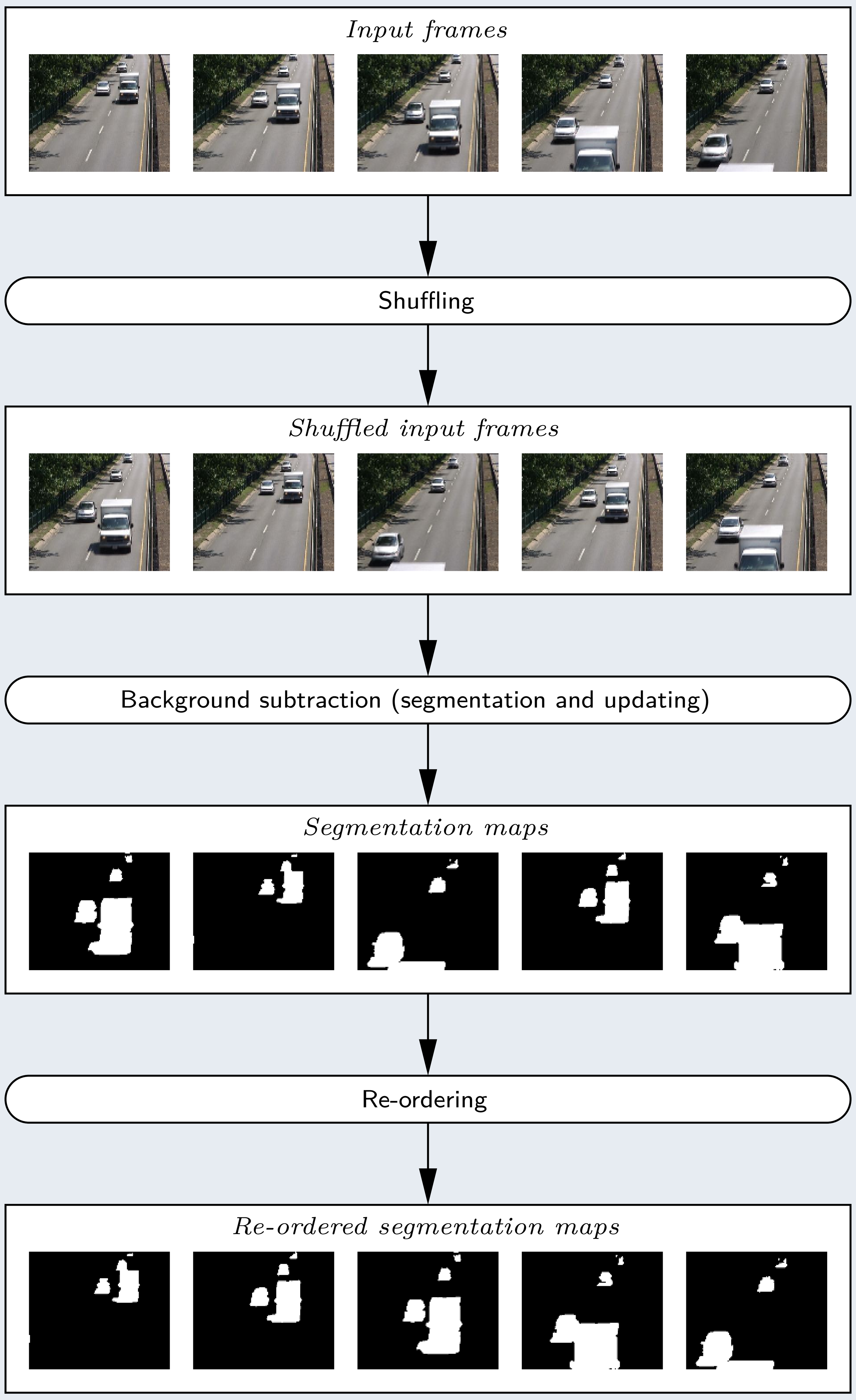

Figure 1 : Flowchart of the proposed time shuffling scheme.

2. Time Shuffling Strategies

Let δ be the difference between any pair of frames, and F_1 and F_2 be two frames. The function δ can be computed as follows:

$$\delta\left(F_1, F_2\right) = \sum_{p \in h \times w} \left|F_1(p) - F_2(p)\right|, \tag{1}$$

where p is a pixel location taken in the frame of size $h \times w$. Taking this definition into account, the challenged time shuffling strategies are the following ones:

- δ_{min}: Minimizes the amount of energy accumulated by δ.
- δ_{max}: Maximizes the amount of energy accumulated by δ.
- **random:** It can be seen as the opposite strategy to the forwards ordering.

3. Experiments

In our experiments, we used the CDnet 2014 dataset. The video sequences are provided with ground truth and are divided among 11 categories: Bad Weather, Baseline, Camera Jitter, Dynamic Background, Intermittent Object Motion, Low Framerate, Night Videos, PTZ, Shadow, Thermal, and Turbulence.

Moreover, we considered 6 background subtraction algorithms: The exponential filter (denoted "Exp. Filter"), the mixture of Gaussians by Stauffer and Grimson ("MoG G."), the mixture of Gaussians by Zivkovic ("MoG Z."), VuMeter by Goyat *et al.*, ViBe by Barnich and Van Droogenbroeck, and SOBS by Maddalena and Petrosino.

4. Results

In Table 1, we present the F_1 scores for the set of background subtraction algorithms applied on the Baseline, Camera Jitter, Intermittent Object Motion, and Thermal categories using all the proposed strategies.

5. Observations and Interpretations

- For the Baseline category, there is no clear winning strategy.
- The δ_{max} strategy is usually not the best one $\rightarrow$ algorithms for background subtraction are intrinsically mainly designed to handle small changes.
- The forwards strategy never wins for the sequences belonging to the Camera Jitter category, and the δ_{min} strategy always improves the segmentation of these sequences $\rightarrow$ shuffling might reduce camera motion between consecutive frames.

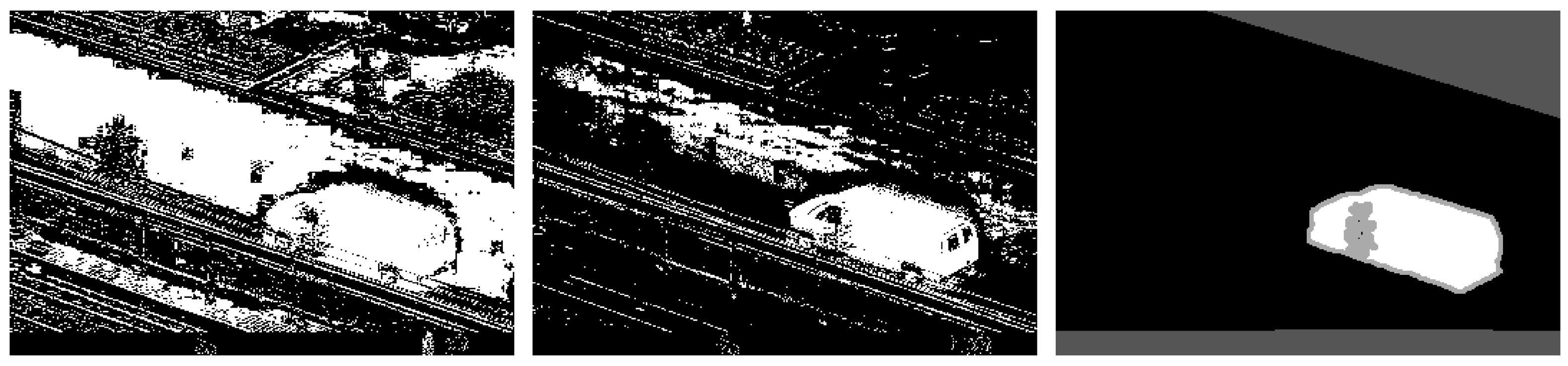

Figure 2 : Segmentation of frame numbered 820 of the *boulevard* sequence (Camera Jitter category) by the MoG G. algorithm using the forwards (left) and δ_{max} (middle) strategies, and the ground truth (right).

- Except for the SOBS algorithm, the forwards strategy is never the best for the video sequences of the Intermittent Object Motion category $\rightarrow$ random and δ_{max} strategies, by interlacing frames with and without stationary objects, might slow down the inclusion of those objects into the background.
- For most methods, the random strategy outperforms the natural ordering in the Thermal category.

Figure 3 : Segmentation of frame numbered 2018 of the *corridor* sequence (Thermal category) by the VuMeter algorithm using the forwards (left) and random (middle) strategies, and the ground truth (right).

- For the VuMeter algorithm, in all cases, at least one shuffling strategy increases the score of the chronological ordering.

6. Conclusion

We examine how changing the time ordering of video frames impacts on the the task of background subtraction. This questions the notion of chronological order and introduces a new view on the problem. Our results remain difficult to interpret since only a subset of algorithms are sensitive to the time ordering. In addition, we observe that, for some categories of video sequences, the chronological ordering is rarely the best one while at least one shuffling strategy systematically improves the F_1 score.

Baseline	Strategy			
Technique	forwards	random	δ_{min}	δ_{max}
Exp. Filter	0.374	0.342	0.374	0.349
MoG G.	0.658	0.657	0.658	0.653
MoG Z.	0.794	0.778	0.791	0.782
VuMeter	0.523	0.572	0.525	0.489
ViBe	0.777	0.801	0.778	0.790
SOBS	0.771	0.710	0.760	0.755

Cam. Jitter	Strategy			
Technique	forwards	random	δ_{min}	δ_{max}
Exp. Filter	0.228	0.222	0.265	0.237
MoG G.	0.452	0.469	0.504	0.505
MoG Z.	0.505	0.505	0.515	0.498
VuMeter	0.486	0.519	0.503	0.498
ViBe	0.542	0.539	0.558	0.537
SOBS	0.437	0.437	0.439	0.443

Int. Obj.	Strategy			
Technique	forwards	random	δ_{min}	δ_{max}
Exp. Filter	0.287	0.306	0.284	0.302
MoG G.	0.426	0.483	0.414	0.454
MoG Z.	0.461	0.490	0.462	0.461
VuMeter	0.197	0.309	0.200	0.204
ViBe	0.408	0.460	0.408	0.431
SOBS	0.514	0.508	0.514	0.508

Thermal	Strategy			
Technique	forwards	random	δ_{min}	δ_{max}
Exp. Filter	0.478	0.607	0.479	0.537
MoG G.	0.519	0.674	0.513	0.612
MoG Z.	0.629	0.632	0.629	0.609
VuMeter	0.292	0.484	0.292	0.309
ViBe	0.520	0.602	0.520	0.563
SOBS	0.763	0.739	0.763	0.669

Table 1 : F_1 scores for different shuffling strategies applied on the Baseline, Camera Jitter, Intermittent Object Motion, and Thermal categories.

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