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Abstract

Dynamic texture (DT) segmentation is the problem of clustering into groups various characteristics and phenomena that reproduce in both time and space, assigning a unique label to each region. Though this problem is highly complex, it has recently become the focus of considerable interest. This paper presents a simple and effective **fusion framework** for dynamic texture segmentation, whose objective is **to combine** multiple and weak region-based segmentation maps to get a final better segmentation result. The different label fields to be fused, are given by a simple clustering technique applied to an input video (based on **three orthogonal planes** xy , xt and yt). This is using as features a set of values of the requantized **local binary patterns (LBP)** histogram around the pixel to be classified. Promising preliminary experimental results have been achieved by our method on the **challenging SynthDB dataset**. Compared to existing dynamic texture segmentation approaches that require estimation of parameters or training classifiers, our method is **easy to implement**, and has **few parameters**.

1. Introduction

- DT segmentation is the problem of clustering into groups various characteristics and phenomena that reproduce in both time and space
- This task consists in assigning a unique label to each group or region
- Highly challenging problem

2. Literature review

In recent years, research on DT segmentation has produced interesting and various methods

- Optical flow estimation + generalized principal component analysis (GPCA)
 - ➔ A decomposition into more than two regions is not supported.
- Convolutional neural networks (CNNs)
 - ➔ Learning and inference are computationally complex

3. Proposed method

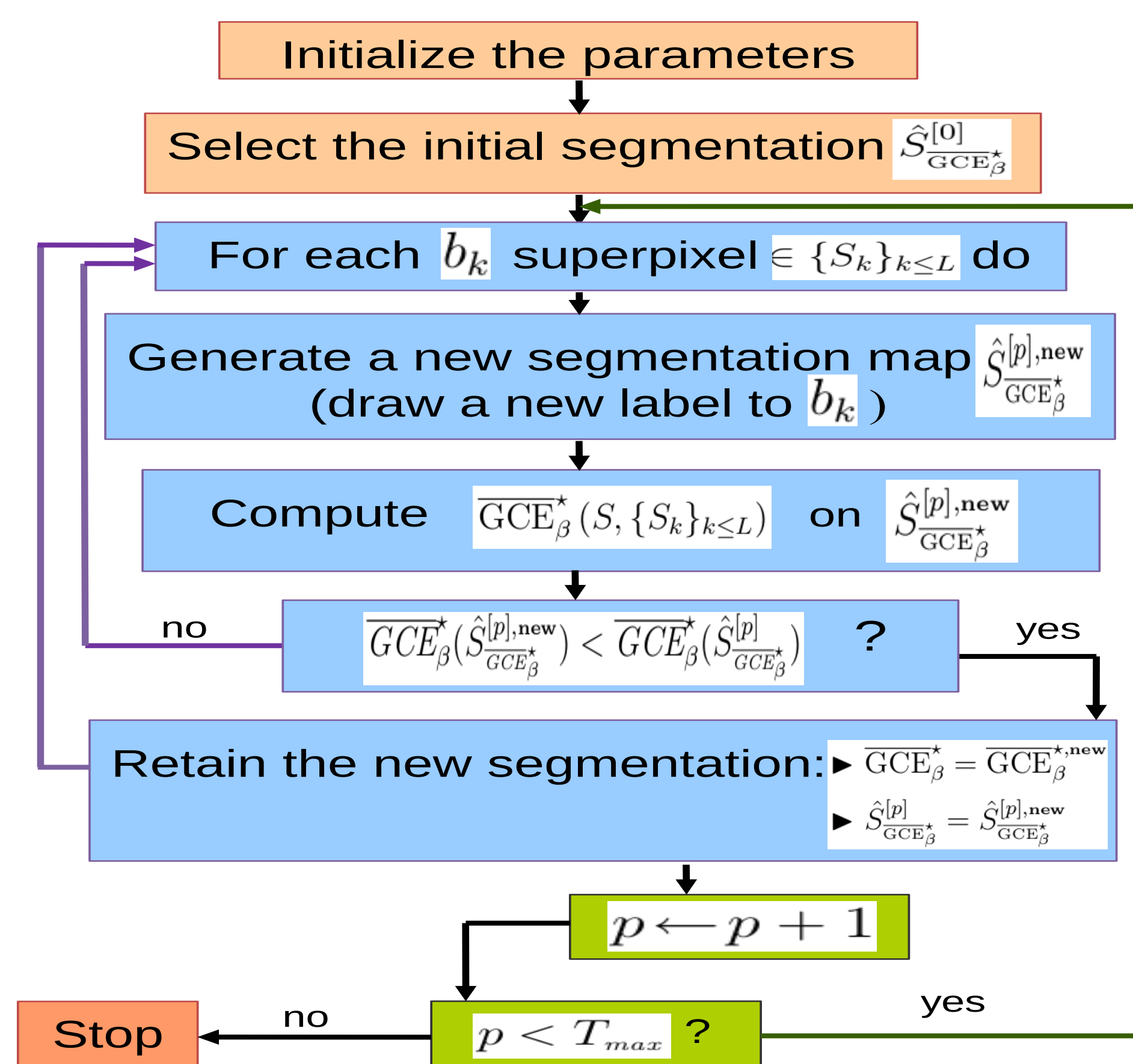
A simple and effective fusion framework

+

A novel energy-minimization model

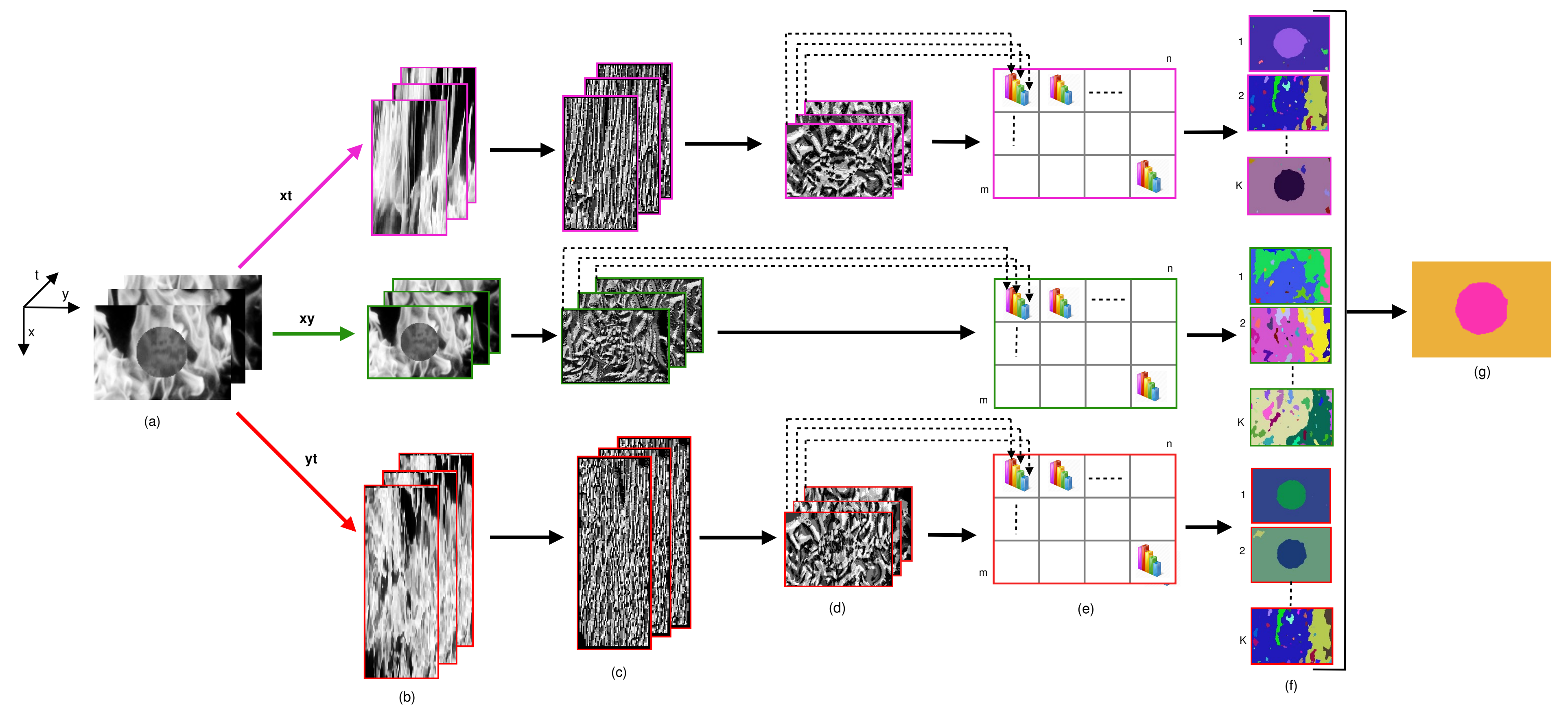
5. Optimization

- Global optimization problem incorporating a nonlinear objective function

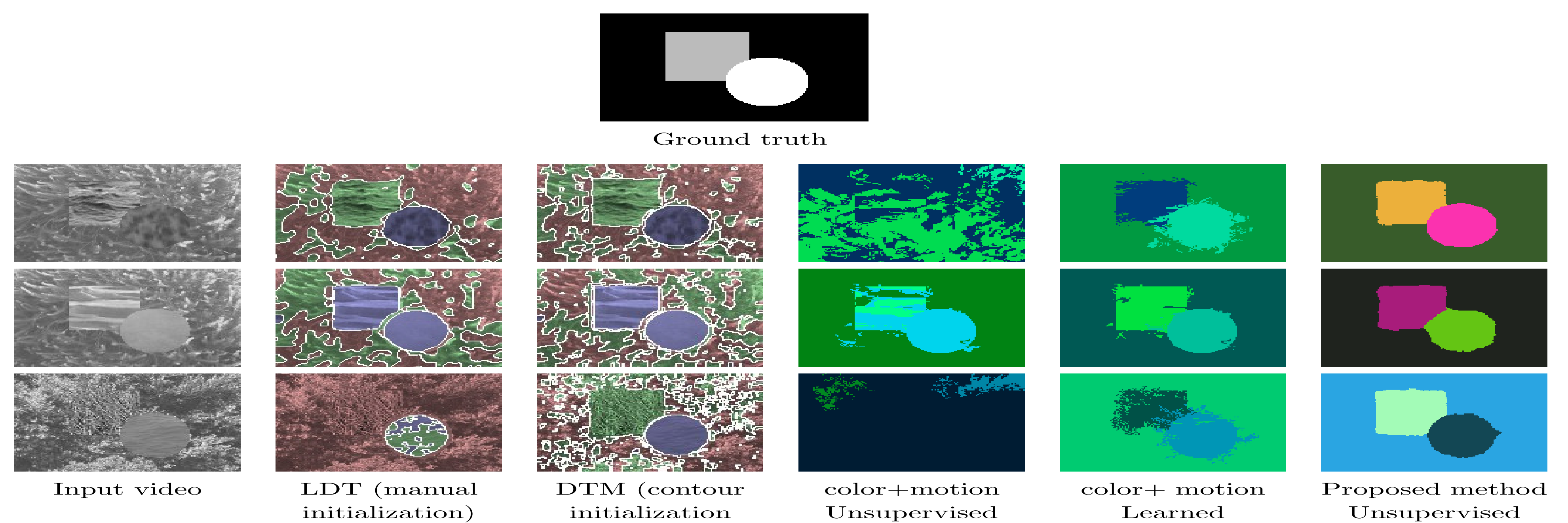


4. Proposed system overview

- Input video
- Slicing step
- LBP representation
- Projection of LBP frames on the xy plan
- Feature extraction and dimensionality reduction
- Clustering with k-means
- Final combined result



6. Results



ALGORITHMS	PERFORMANCE (Avg. PR)		
	99 videos 2 labels	100 videos 3 labels	100 videos 4 labels
GPCA [1]	0.515	0.477	0.526
DTM [2]	0.907	0.847	0.859
Color + motion (unsupervised) [3]	N/A	0.727	N/A
Color + motion (learned, logistic regression) [3]	N/A	0.771	N/A
-Proposed method-	0.953	0.855	0.796

7. Conclusions

We propose a new approach for video segmentation with dynamic textures:

- Our method combine (based on a new geometric criterion) multiple and weak region-based segmentation maps to get a final better segmentation result
- Experiments show that our results are comparable and even improve on state of the art methods using unsupervised and supervised strategy

References

- [1] R. Vidal, and A. Ravichandran. Optical flow estimation and segmentation of multiple moving dynamic textures. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 516–521, 2005.
- [2] A. B. Chan, and N. Vasconcelos. Modeling clustering and segmenting video with mixtures of dynamic textures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(5): 909–926, 2008.
- [3] D. Teney, M. Brown, D. Kit, and P. Hall. Learning similarity metrics for dynamic scene segmentation. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2084–2093, 2015.