GraphBGS: Background Subtraction via Recovery of Graph Signals

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Motivation and Problem

- Deep learning approaches require large amounts of data to avoid overfitting.
- Graphs offer tools to exploit the geometrical structure of data.
- Most deep learning techniques in background subtraction do not evaluate their performance on unseen videos.

Motivation

- Data Hungry
- Geometric Information

- Capturing geometrical information with graphs

Problem

- Background subtraction, moving object detection

- Background subtraction of unseen videos using semi-supervised learning techniques inspired from graph signal processing.

Algorithm

- Our proposed algorithm consists of several components including:
  - Instant segmentation using Cascade Mask R-CNN [Cal and Vasconcelos (2019)]
  - Background initialization using a temporal median filter [Piccardi (2004)]
  - Feature extraction with motion [Lucas et al. (1981)], texture [Ojala et al. (2002)], and intensity features
  - Semi-supervised learning inspired from Sobolev norm minimization.

Overview

- Pipeline of our algorithm

Instances and Graph

- Instance masks are mapped as nodes of a graph G.
- The representation of the nodes is given by:
  - Motion features
  - Texture features
  - Intensity features
  - Background features.
- The graph is constructed with a k-nearest neighbors with k = 30.
- The graph signal associated to the problem of background subtraction is sampled for a evaluation with unseen videos.

Experimental Framework

- Some visual results on CDNet2014.

<table>
<thead>
<tr>
<th>Category</th>
<th>Original</th>
<th>Ground Truth</th>
<th>SubSTU2014</th>
<th>PASCAL</th>
<th>ITB-ET</th>
<th>ST-Net</th>
<th>GraphNet</th>
<th>Epochs</th>
</tr>
</thead>
<tbody>
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Comparisons of average F-measure in CDNet2014: The best and second best performing method for each challenge are shown in red and blue, respectively.

Summary and Future Work

- This work introduces concepts of graph signal processing in the problem of background subtraction.
- Our algorithm is composed of: a Cascade Mask R-CNN for instance segmentation, a temporal median filter for background initialization, feature extraction for node representation, a k-nearest neighbors for graph construction, and minimization of the Sobolev norm of graph signals for the semi-supervised learning algorithm.
- For future work:
  - A generalized theory of graph signal processing [Ji and Tay (2018)] can be used to extend the graph signals to fuzzy concepts [E Jia et al. (2008)], leading to a richer representation of moving and static objects.
  - Another important direction is to study an inductive framework [Hamilton et al. (2017)] for GraphBGS, trying to get a real-time implementation of GraphBGS [Croppa et al. (2020)].
  - Perhaps, concepts of graph signal processing such as active semi-supervised learning [Anis et al. (2013)] could lead to new developments in the field of computer vision and end-to-end architectures for video analysis with semi-supervised learning.