GraphBGS: Background Subtraction via Recovery of Graph Signals

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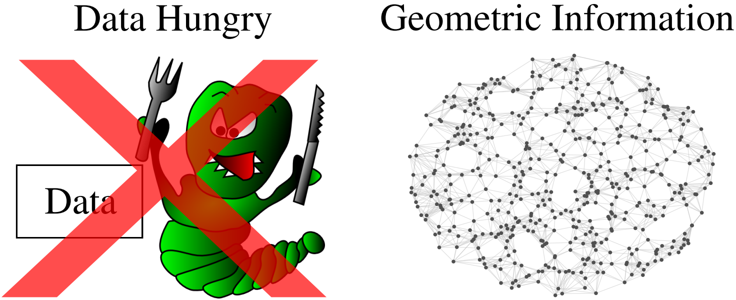
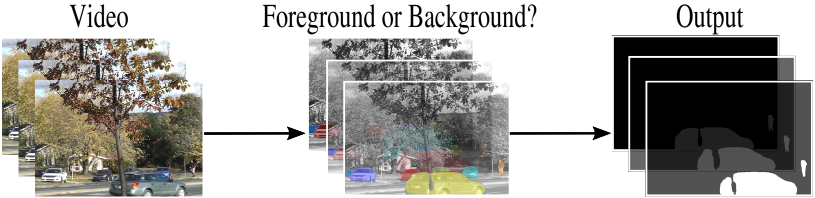
Motivation and Problem

Motivation



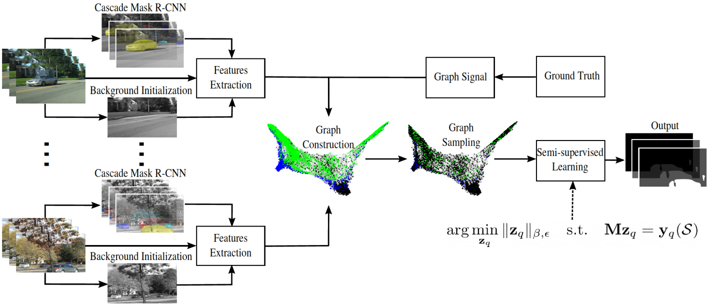
Capturing geometrical information with graphs

- 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.



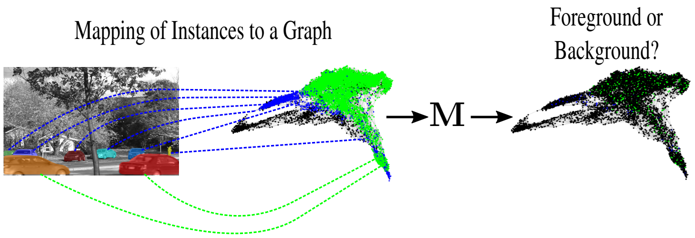
Background subtraction, moving object detection

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



Pipeline of our algorithm

- Our proposed algorithm consists of several components including:
  - Instance segmentation using Cascade Mask R-CNN [Cai 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.

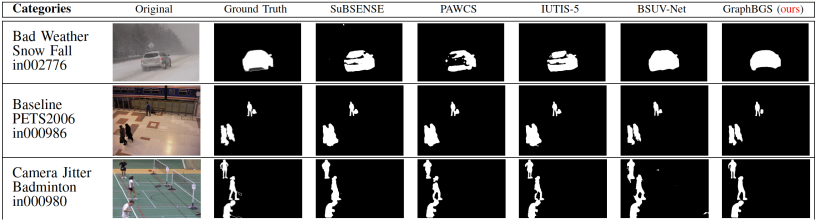


Cascade Mask R-CNN, nodes representation, sampling.

- 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 neighboors with k$=30$.
- The graph signal associated to the problem of background subtraction is sampled for a evaluation with unseen videos.

Experimental Framework

Results I



Some visual results on CDNet2014.

Challenge	FTSG	SuBSENSE	PAWCS	WisenetMD	IUTIS-5	SemanticBGS	FgSegNet v2	BSUV-Net	GraphBGS
Bad Weather	0.8228	0.8619	0.8152	0.8616	0.8248	0.8260	0.7952	**0.8713**	**0.9085**
Baseline	0.9330	0.9503	0.9397	0.9487	0.9567	**0.9604**	0.6926	**0.9693**	0.9535
Camera Jitter	0.7513	0.8152	0.8137	0.8228	0.8332	**0.8388**	0.4266	0.7743	**0.8826**
Dynamic-B	0.8792	0.8177	**0.8938**	0.8376	0.8902	**0.9489**	0.3634	0.7967	0.8353
I-O Motion	**0.7891**	0.6569	0.7764	0.7264	0.7296	**0.7878**	0.2002	0.7499	0.5036
Low-F rate	0.6259	0.6445	0.6588	0.6404	**0.7743**	**0.7888**	0.2482	0.6797	0.6022
PTZ	0.3241	0.3476	0.4615	0.3367	0.4282	0.5673	0.3503	**0.6282**	**0.7993**
Shadow	0.8832	0.8986	0.8913	0.8984	0.9084	**0.9478**	0.5295	0.9233	**0.9712**
Thermal	0.7768	0.8171	0.8324	0.8152	0.8303	0.8219	0.6038	**0.8581**	**0.8594**
Overall	0.7539	0.7566	0.7870	0.7653	0.7923	**0.8320**	0.4158	0.8056	**0.8128**

Comparisons of average F-measure in CDNet2014. The best and second best performing method for each challenge are shown in **red** and **blue**, respectively.

- 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 y to fuzzy concepts [El Baf 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 [Cioppa et al. (2020)].
  - Perhaps, concepts of graph signal processing such as active semi-supervised learning [Anis et al. (2018)] could lead in new developments in the field of computer vision and end-to-end architectures for video analysis with semi-supervised learning.

Thanks.
Questions?

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TABLE III: Comparison of F-measure results over the videos of UCSD background subtraction dataset. The best and second best performing methods for each video are shown in **red** and **blue**, respectively.

Sequence	DECOLOR	ViBe	3WD	GRASTA	SuBSENSE	ROSL	ADMM	OR1MP	BSUV-Net	GraphBGS
Birds	0.1457	0.3354	0.1308	0.1320	**0.4832**	0.1478	0.0227	0.1394	0.2625	**0.7143**
Boats	0.2179	0.1854	0.1576	0.0678	0.4550	0.1637	0.1212	0.1100	**0.6621**	**0.7594**
Bottle	0.4765	0.4512	0.1364	0.1159	0.6570	0.2069	**0.6589**	0.1795	0.5039	**0.8741**
Chopper	0.6214	0.4930	0.3171	0.0842	**0.6723**	0.2920	0.1250	0.2653	0.3020	**0.6956**
Cyclists	0.2224	0.1211	0.1003	0.1243	0.1445	0.1366	0.1093	0.1242	**0.4138**	**0.7330**
Flock	0.2943	0.2306	0.2007	0.1612	0.2492	**0.3409**	0.1088	0.2605	0.0025	**0.5872**
Freeway	**0.5229**	0.4002	0.5028	0.0814	**0.5518**	0.3875	0.0816	0.1549	0.1185	0.3491
Hockey	0.3449	0.4195	0.2789	0.3149	0.3611	0.4106	0.2981	0.4296	**0.6908**	**0.7608**
Jump	0.3135	0.2636	0.2481	0.4175	0.2295	0.4198	0.0609	0.3073	**0.8697**	**0.7727**
Landing	0.0640	0.0433	0.0457	0.0414	0.0026	0.0506	**0.0826**	0.0442	0.0012	**0.1822**
Ocean	0.1315	0.1648	0.2055	0.1144	0.2533	0.1422	0.1809	0.1252	**0.5335**	**0.8593**
Peds	**0.7942**	0.5257	0.7536	0.4653	0.5154	0.7418	0.6667	0.4297	0.6738	**0.8465**
Skiing	**0.3473**	0.1441	0.1981	0.0927	0.2482	0.1942	0.0519	0.1791	0.0602	**0.5333**
Surf	**0.0647**	0.0462	0.0579	0.0523	0.0467	0.0453	0.0162	0.0317	0	**0.5302**
Surfers	0.1959	0.1189	0.0962	0.0742	0.1393	0.1184	0.1950	0.1044	**0.4776**	**0.6400**
Trafic	**0.2732**	0.1445	0.2032	0.0368	0.1165	0.1042	0.1044	0.0882	0	**0.5722**
Overall	0.3144	0.2555	0.2271	0.1485	0.3203	0.2439	0.1803	0.1858	**0.3483**	**0.6506**