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Introduction

Input





Two images of semantically related but different object instances from similar views

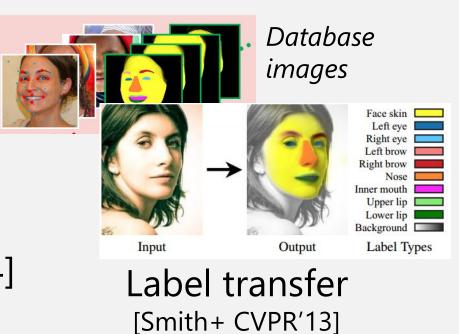


Output

- We propose a method to simultaneously recover cosegmentation and correspondence (or flow) maps.
- Our joint formulation improves performance on both tasks; more accurate than existing methods that solve either task.

Applications

- 3D reconstruction from object categories [Vicente+ CVPR'14]
- Non-parametric scene parsing [Liu+ TPAMI'11, Smith+ CVPR'13, Karsch+ TPAMI'14]



Contributions

New dataset with ground truth/evaluation toolkit

• 400 image pairs, 7 object categories

New joint model and inference technique

- Discrete-continuous labeling problem for flow and segmentation estimation in a hierarchical MRF model.
- Joint inference of hierarchical structure and labeling via an energy minimization framework using iterated graph cuts.
- Recovers layered structure of nested image regions.

Joint Recovery of Dense Correspondence and Cosegmentation in Two Images

Common object cosegmentation (binary mask) and dense flow map that aligns the common region in the images

http://taniai.space/..



Hierarchical (layered graph) model

 $F(G, f, \alpha) = E_{\text{graph}}(G) + E_{\text{flow}}(f|G) + E_{\text{seg}}(\alpha|G) + E_{\text{reg}}(f, \alpha|G)$

Graph structure term

Flow data term

Layer K

Layer 2

Layer 1 (final result)



- Node sparsity Color consistency
- of superpixels



FG/BG color likelihood (learned during initialization)

- HOG features for appearance matching
- Similarity transform

Why hierarchy? We need *powerful regularization* to be robust against significant appearance dissimilarity of different object instances.

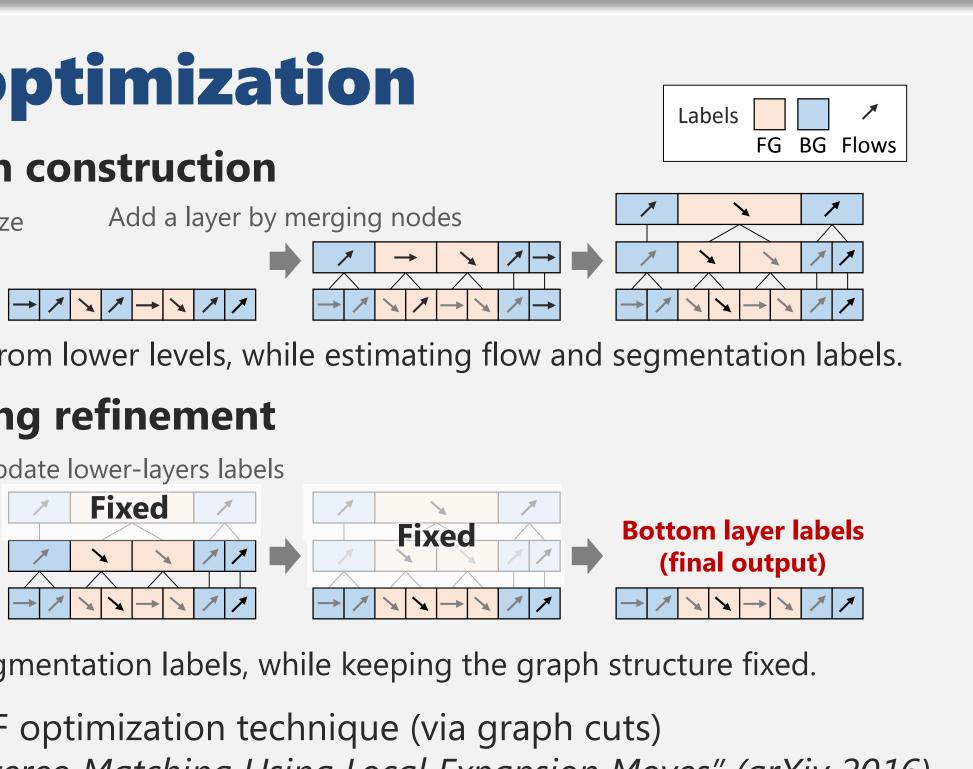
Why not precompute hierarchical structure? A good hierarchical structure must respect object boundary and smoothness of the flow map. However, these are not available a priori and thus, jointly inferred with the flow and segmentation.

Two-step optimization

1) Bottom-up graph construction

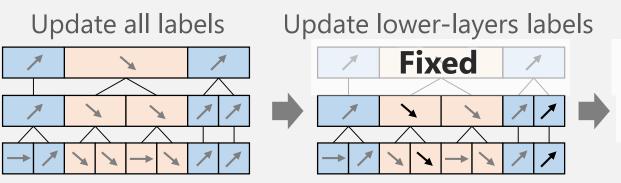
Bottom layer nodes

Add a layer by merging nodes



Incrementally add layers from lower levels, while estimating flow and segmentation labels.

2) Top-down labeling refinement



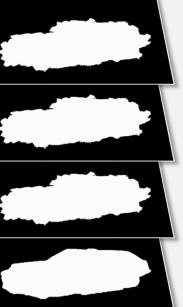
Update flow and segmentation labels, while keeping the graph structure fixed.

Based on continuous MRF optimization technique (via graph cuts) Taniai+. "Continuous Stereo Matching Using Local Expansion Moves" (arXiv 2016)

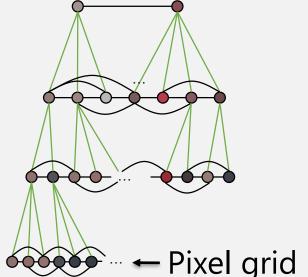
Yoichi Sato (The University of Tokyo)

Cosegmentation

data term



Pairwise smoothness term

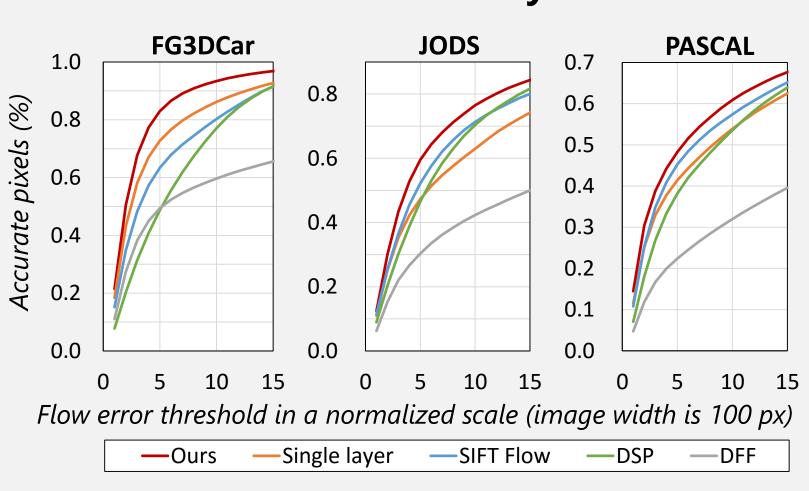


• Spatial neighbors Parent child edges

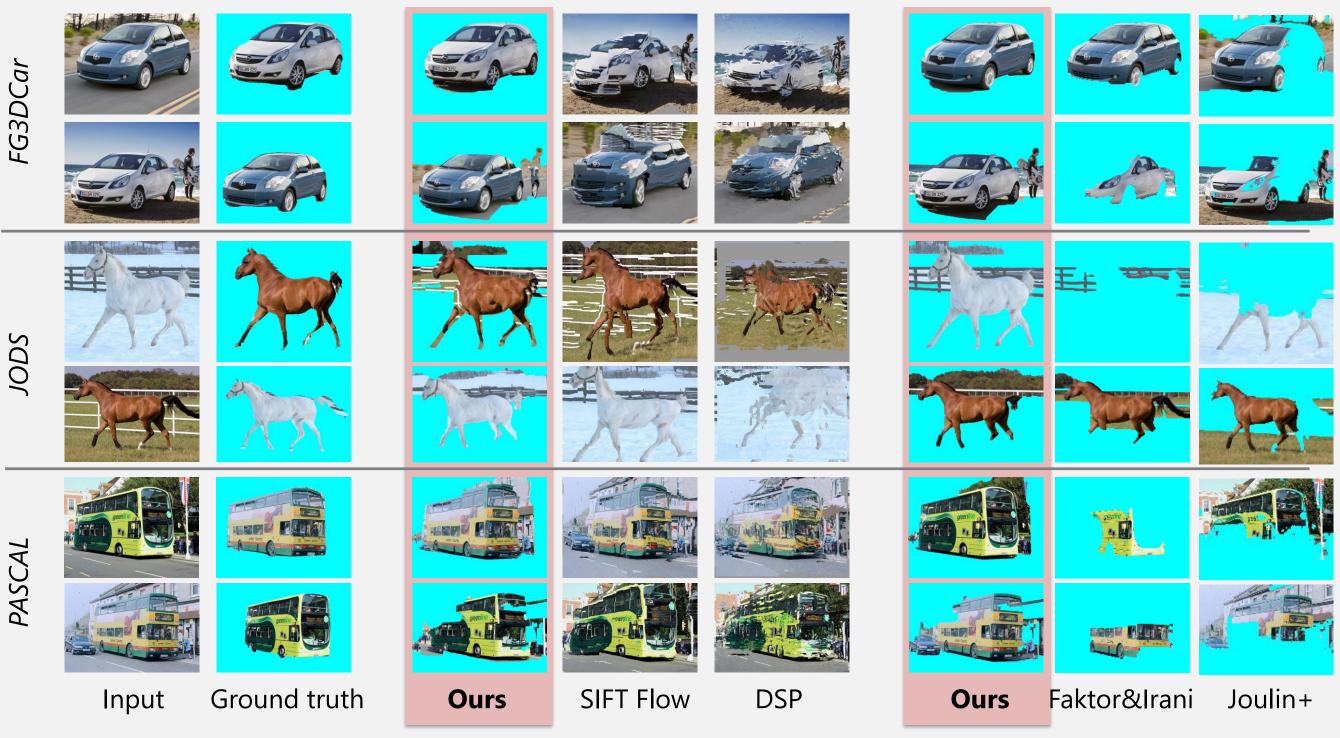
Experiments

Methods	Flow	Coseg.	Regularization
Our method	 Image: A start of the start of	 ✓ 	Hierarchical MRF
Our method (no hierarchy)	~	v	2D MRF
SIFT flow [Liu+ TPAMI'11]	~		2D MRF
DSP [Kim+ CVPR'13]	~		Pyramid hierarchy
DAISY filter flow [Yang+ CVPR'14]	~		No explicit regularization
Faktor & Irani [ICCV'11]		~	
Joulin+ [CVPR'10]		~	

Flow accuracy



Input





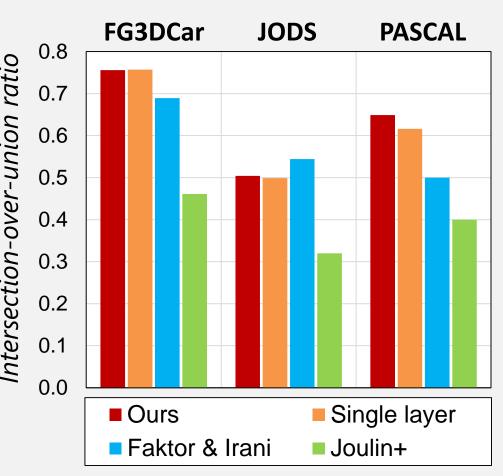
CVPR2016 Microsoft[®] Research

Dataset info

Images in our dataset are grouped by their source

- **FG3DCar** [Lin+ '14]
- JODS [Rubinstein+ '13]
- **PASCAL** [Hariharan+ '11]

Cosegmentation accuracy



Flow (correspondence)

Cosegmentation