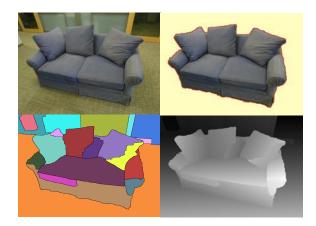
# Multiple View Object Cosegmentation using Appearance and Stereo Cues

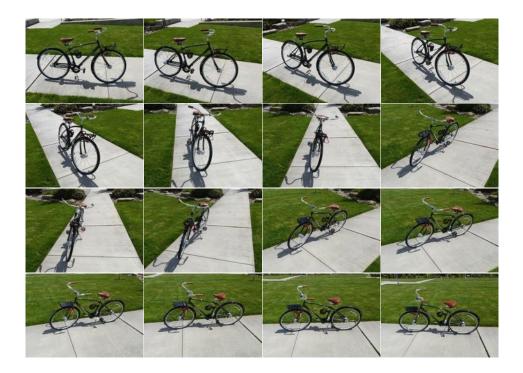
Adarsh Kowdle<sup>1</sup>

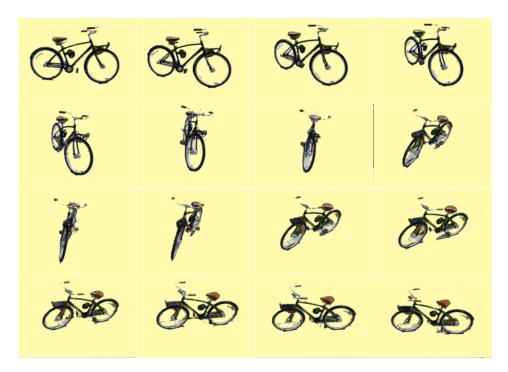
Sudipta Sinha<sup>2</sup>

Richard Szeliski<sup>2</sup>



<sup>1</sup>Cornell University, <sup>2</sup>Microsoft Research





#### Final result using our approach

# **Previous Work**

#### Interactive (co)-segmentation





GrabCut - Rother et. al. SIGGRAPH '04





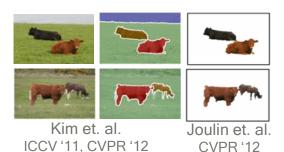
iCoseg - Batra et. al. IJCV '11

iModel - Kowdle et. al. ECCV - RMLE '10

#### Unsupervised cosegmentation



Mukherjee et. al. Vicente et. al. CVPR '11 CVPR '11



# **Previous Work**

Unsupervised 3D reconstruction and cosegmentation





Campbell et. al. BMVC '07, CVMP '11

Piecewise planar stereo and low-level segmentation





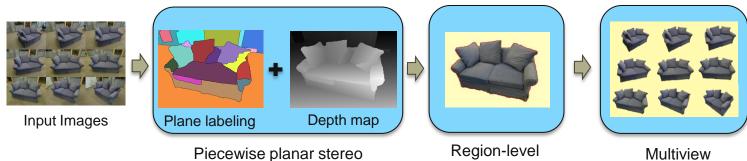
Birchfield et. al. Sinha et. al. ICCV '99 ICCV '09 Bleyer et. al. CVPR '11

#### Contributions

- Unsupervised object cosegmentation algorithm
  - exploits stereo and appearance cues

- Extend prior work on piecewise planar stereo
  - robust to scenarios where stereo matching is unreliable

#### **Overview**



FG/BG labeling

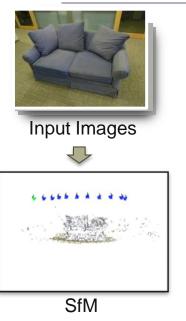
FG/BG labeling

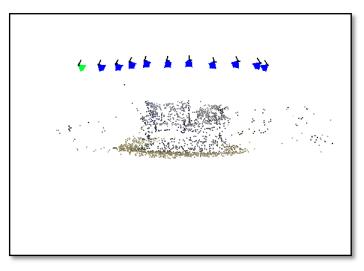
#### **Overview**



FG/BG labeling

Multiview FG/BG labeling

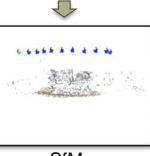




Structure from Motion (SfM)



Input Images



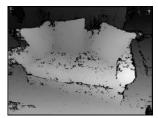




SGM Stereo

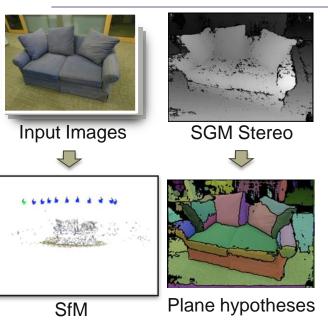


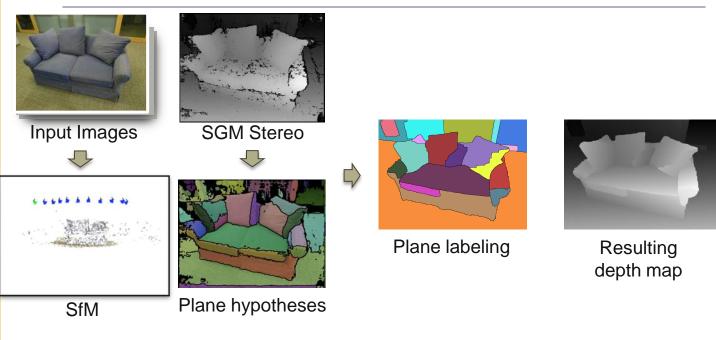




Semi-global matching (SGM Stereo) [Hirschmüller 2008]













SGM Stereo Bicycle sequence

Piecewise planar depthmap Only stereo cues Sinha *et. al.* 2009 Our approach Appearance and stereo cues

Pixel level MRF Grid graph over all pixels p

$$l_p \in \Pi = \{\pi_i\}$$

Each plane  $\pi_i$  is parameterized by

- 1. 3D plane equation
- 2. Appearance model (  $A_i$  )

$$E(L) = \sum_{p \in P} E_p^A(l_p) + \lambda_G \sum_{p \in P} c_p E_p^G(l_p) + \lambda_S \sum_{(p,q) \in \mathcal{N}} E_{pq}(l_p, l_q)$$

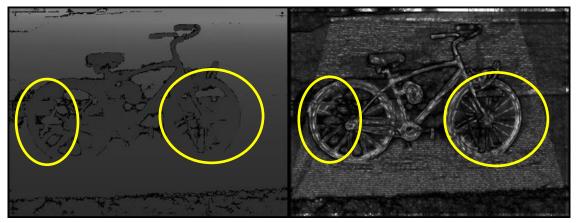
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Per-pixel confidence



#### SGM Stereo

#### Confidence map

$$E(L) = \sum_{p \in P} E_p^A(l_p) + \lambda_G \sum_{p \in P} c_p E_p^G(l_p) + \lambda_S \sum_{(p,q) \in \mathcal{N}} E_{pq}(l_p, l_q)$$

Appearance unary term



Appearance model Lab features (GMM)  $\mathbf{A}_i$ 

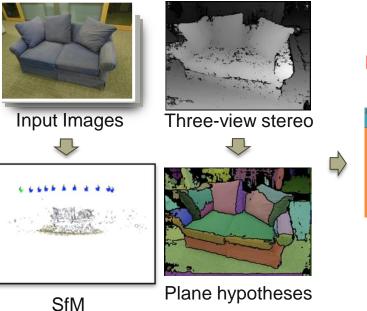
 $E_p^A(l_p = \pi_i) = -log(p(\mathbf{x}|\mathbf{A}_i))$ 

Per-region color models vs. global color models

 $E(L) = \sum E_p^A(l_p) + \lambda_G \sum c_p E_p^G(l_p) + \lambda_S \sum E_{pq}(l_p, l_q)$  $p \in P$  $p \in P$  $(p,q) \in \Lambda$ 

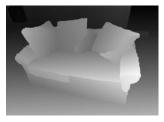
Pairwise term

Contrast sensitive Potts Model



#### Iterative graph cut with alpha-expansion (Typically 2-3 iterations)



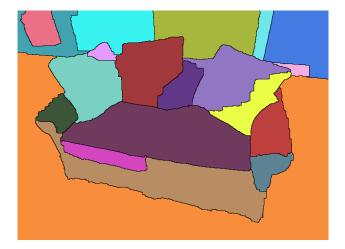


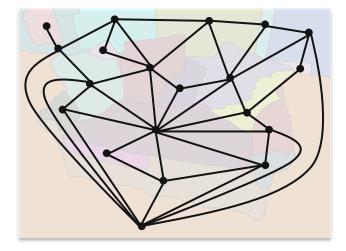
Plane labels

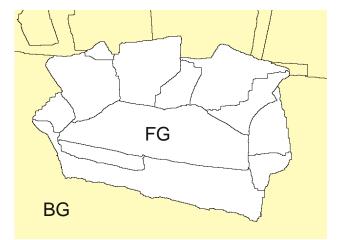
Piecewise planar depth map

#### **Overview**





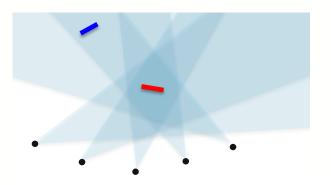


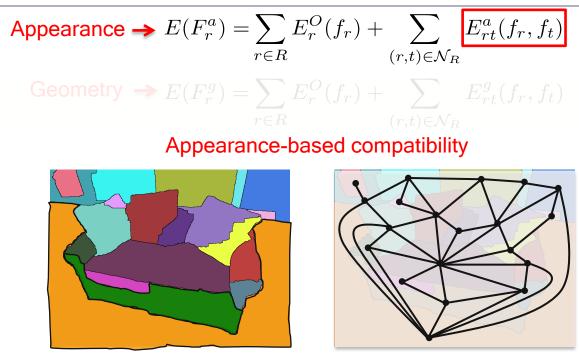


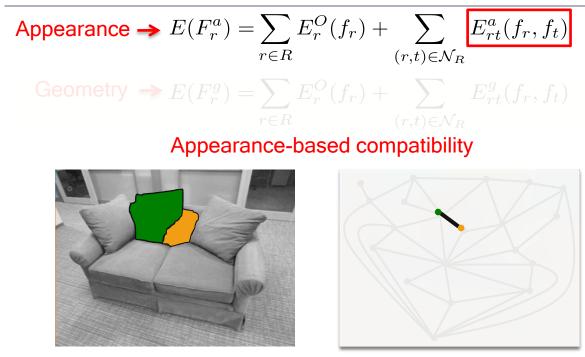
#### **Region level labeling**

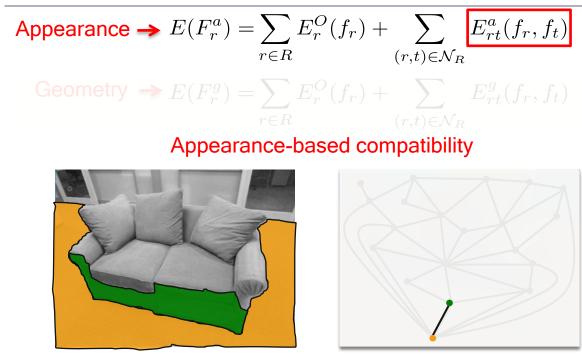
Appearance 
$$\Rightarrow E(F_r^a) = \sum_{r \in R} E_r^O(f_r) + \sum_{(r,t) \in \mathcal{N}_R} E_{rt}^a(f_r, f_t)$$
  
Geometry  $\Rightarrow E(F_r^g) = \sum_{r \in R} E_r^O(f_r) + \sum_{(r,t) \in \mathcal{N}_R} E_{rt}^g(f_r, f_t)$   
Objectness term

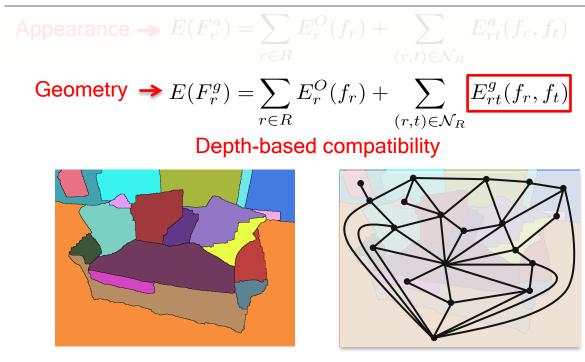


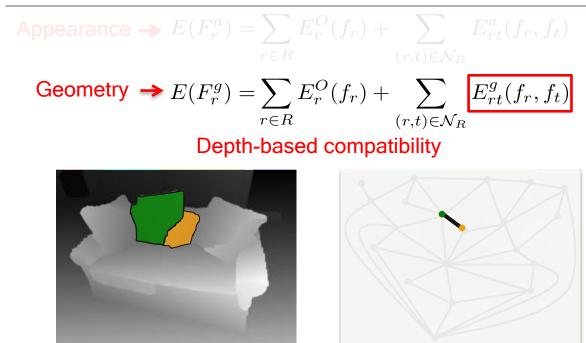


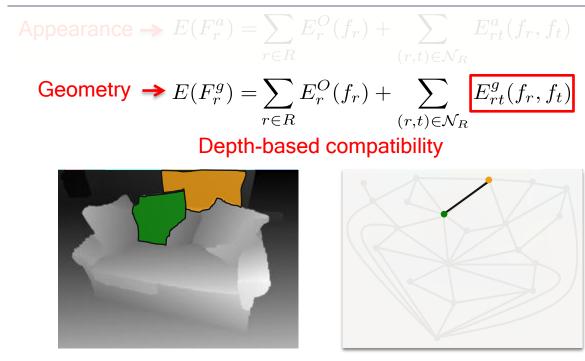








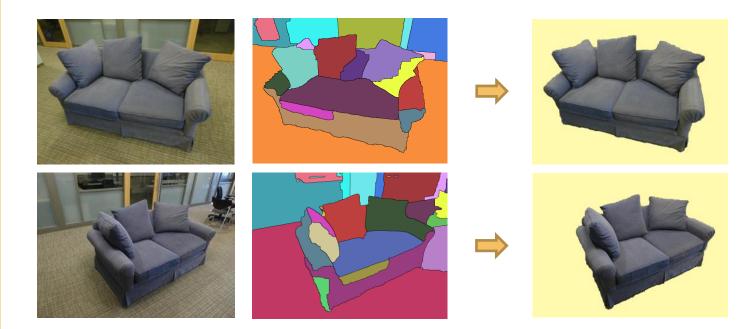




Appearance 
$$\rightarrow E(F_r^a) = \sum_{r \in R} E_r^O(f_r) + \sum_{(r,t) \in \mathcal{N}_R} E_{rt}^a(f_r, f_t)$$
  
Geometry  $\rightarrow E(F_r^g) = \sum_{r \in R} E_r^O(f_r) + \sum_{(r,t) \in \mathcal{N}_R} E_{rt}^g(f_r, f_t)$ 

# Graph cut on each energy function independently to obtain MAP labels

Region labeled FG if either solutions label region FG

















#### **Overview**



FG/BG labeling

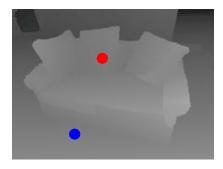
FG/BG labeling

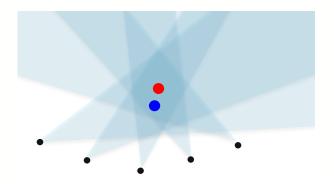
#### **Multiview FG/BG labeling**

Pixel level MRF Grid graph over all pixels p

$$E(F) = \sum_{p \in P} E_p^O(f_p) + \sum_{p \in P} E_p^A(f_p) + \sum_{(p,q) \in \mathcal{N}} E_{pq}(f_p, f_q)$$

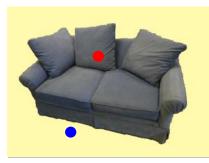
#### Objectness term



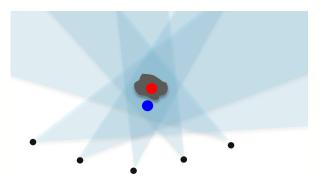


$$E(F) = \sum_{p \in P} E_p^O(f_p) + \sum_{p \in P} E_p^A(f_p) + \sum_{(p,q) \in \mathcal{N}} E_{pq}(f_p, f_q)$$

**Objectness term** 



Region-level FG/BG labeling



 $E(F) = \sum_{p \in P} E_p^O(f_p) + \sum_{p \in P} E_p^A(f_p) + \sum_{(p,q) \in \mathcal{N}} E_{pq}(f_p, f_q)$ Appearance unary term  $\mathbf{A} = \{\mathbf{A}_f, \mathbf{A}_b\}$ FG

Region-level FG/BG labeling

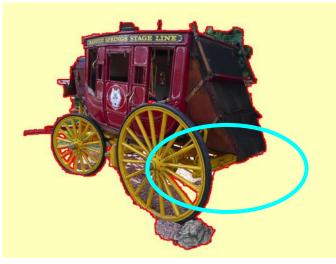
BG

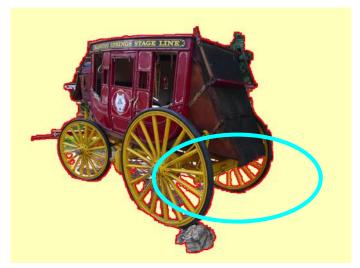
$$E(F) = \sum_{p \in P} E_p^O(f_p) + \sum_{p \in P} E_p^A(f_p) + \sum_{(p,q) \in \mathcal{N}} E_{pq}(f_p, f_q)$$

Pairwise term

Contrast sensitive Potts Model

#### Graph cut to obtain MAP labels

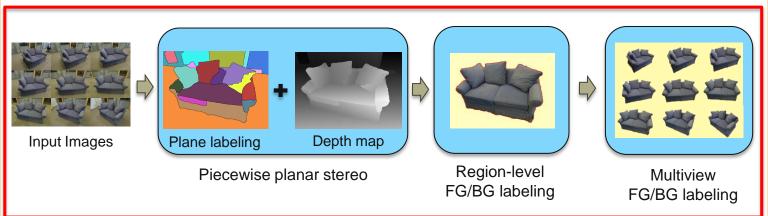




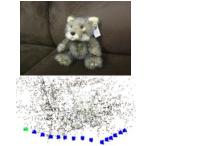
#### Region-level FG/BG labeling

Multiview FG/BG labeling

## **Overview**



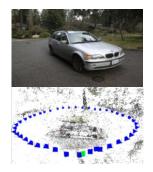
#### **Datasets**

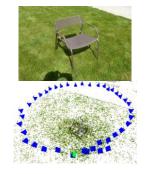














#### Ground truth: Manually labeled using GrabCut



#### Ground truth: Manually labeled using GrabCut



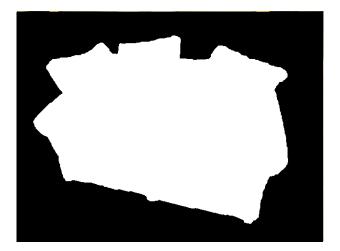


#### 4 minutes

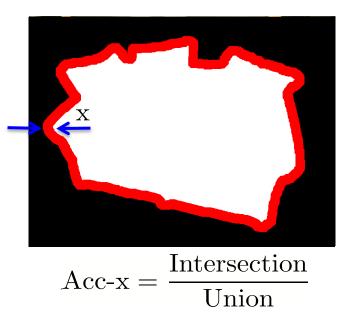
#### **Evaluation metric**



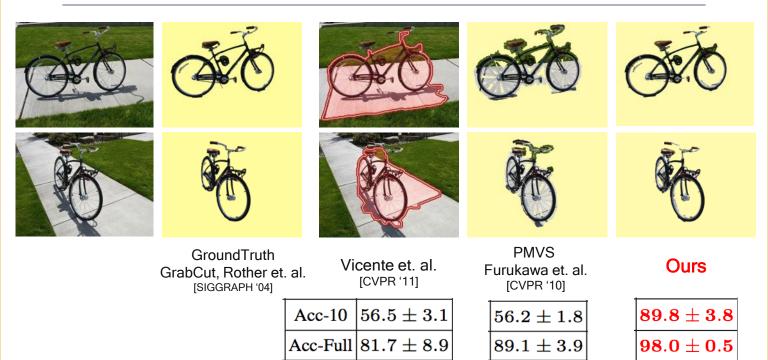
#### **Evaluation metric**



#### **Evaluation metric**



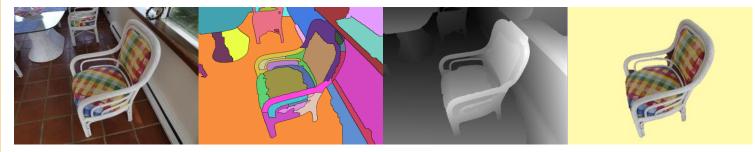
# Comparisons

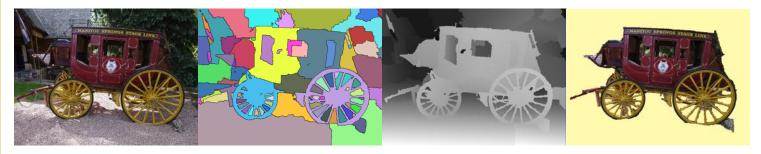


# Comparisons

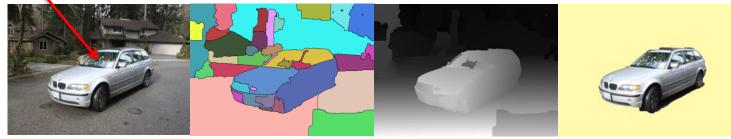
Name		Vicente'11	PMVS'12	Ours
Βικε	Acc-10	$68.1\pm6.7$	$61.0\pm3.9$	$\textbf{90.0} \pm \textbf{4.9}$
	Acc-Full	$88.9\pm6.3$	$96.0 \pm 1.8$	$99.1 \pm 0.7$
BICYCLE	Acc-10	$56.5\pm3.1$	$56.2 \pm 1.8$	$89.8 \pm 3.8$
	Acc-Full	$81.7\pm8.9$	$89.1\pm3.9$	$98.0 \pm 0.5$
CHAIR1	Acc-10	$73.3\pm4.8$	$72.7\pm2.1$	$\textbf{93.9} \pm \textbf{3.1}$
	Acc-Full	$86.9\pm7.8$	$96.6\pm0.4$	$99.2 \pm 0.4$
CAR	Acc-10	$74.4 \pm 5.3$	$\overline{59.6 \pm 4.3}$	$\textbf{83.2} \pm \textbf{1.1}$
	Acc-Full	$91.8\pm4.3$	$91.2\pm5.5$	$\textbf{97.9} \pm \textbf{0.6}$

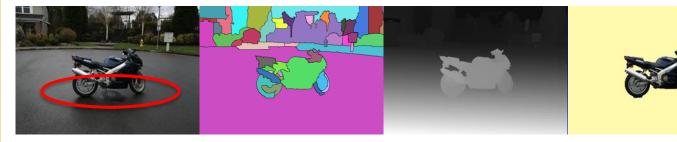
#### Complicated object structures modeled via piecewise planar proxies



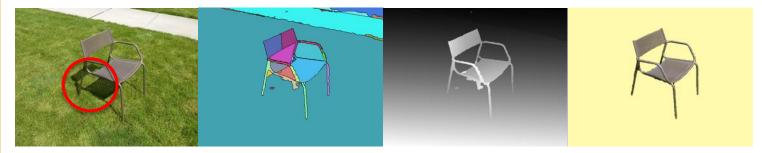


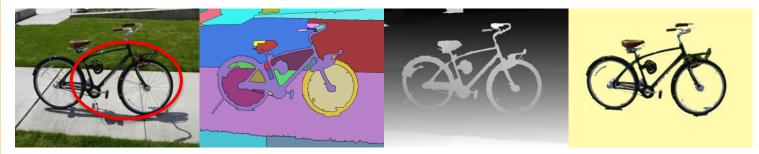
Irregularities such as specular surfaces and overlapping FG/BG appearance models





#### Complex occlusions and thin structures





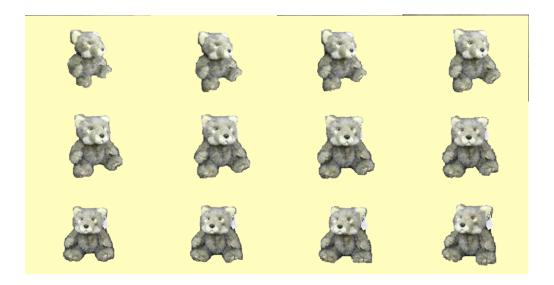
# Conclusions

- Unsupervised cosegmentation algorithm that uses appearance and stereo cues to:
  - infer object of interest
  - recover pixel-accurate foreground segmentation in each view
  - recover good quality depth maps

# Thank you



### **Additional Results**



#### **Teddy sequence**