Object Co-skeletonization with Co-segmentation

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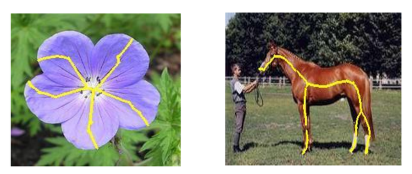
Introduction

Goal: To exploit joint processing to extract objects' skeletons in images of the same category, which is also known as object co-skeletonization.

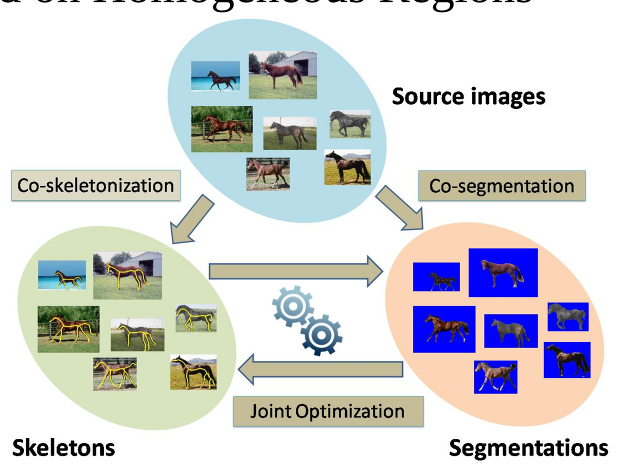
Challenges:

Sensitive to Unsmooth Segmentations



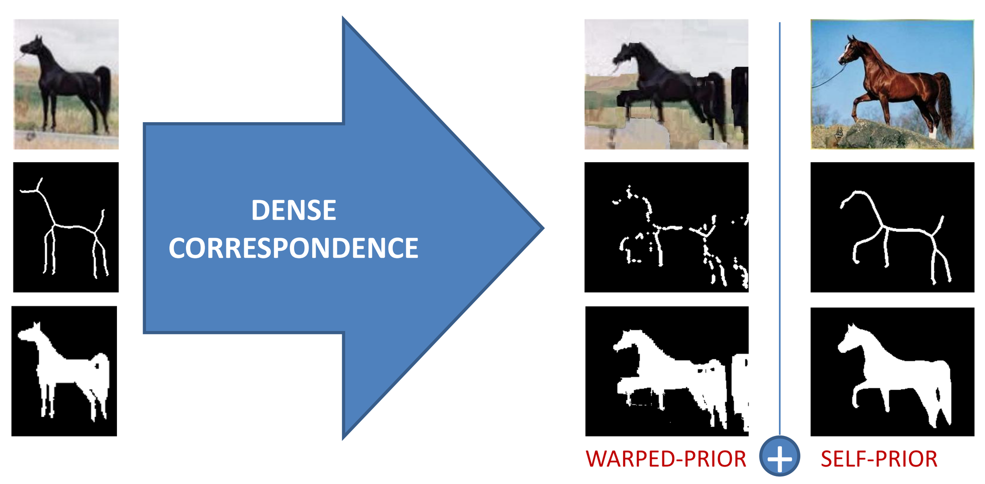
Placed on Homogeneous Regions

This Paper: Leveraging existing co-segmentation idea to help perform co-skeletonization such that both the tasks help each other synergistically. Segmentation provides the required shape information for skeletonization, and skeletonization provides the required scribble information for segmentation.

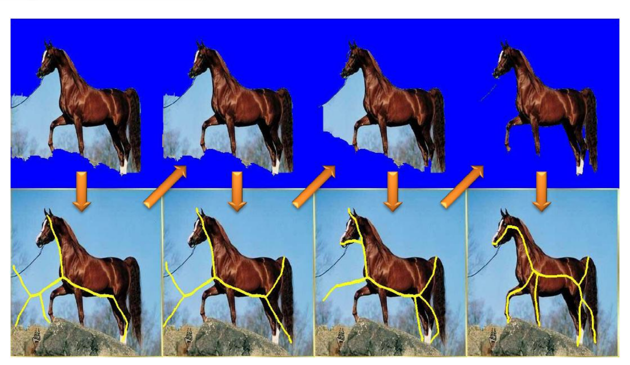


Proposed Method

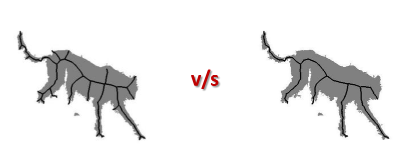
Joint Processing:



Interdependence:



Smoothness: Typical spatial neighborhood smoothness and simplicity in segmentation and skeletonization, respectively.



Formulation

$$\min_{K_i,O_i} \lambda\psi_{pr}(K_i,O_i|\mathcal{N}_i)+\psi_{in}(K_i,O_i|I_i)+\psi_{sm}(K_i,O_i|I_i)$$
$$s.t.\ K_i \subseteq \mathbf{ma}(O_i) \quad (1)$$

Skeleton Pruning Problem

$$\min_{K_i} \lambda\psi_{pr}^{k}(K_i|\mathcal{N}_i)+\psi_{in}^{k}(K_i|O_i)+\psi_{sm}^{k}(K_i) \quad (2)$$
$$s.t.\ K_i \subseteq \mathbf{ma}(O_i).$$

For Co-skeletonization

Interactive Segmentation Problem

$$\min_{O_i} \lambda\psi_{pr}^{o}(O_i|\mathcal{N}_i)+\psi_{in}^{o}(O_i|K_i,I_i)+\psi_{sm}^{o}(O_i|I_i). \quad (3)$$

For Co-segmentation

Algorithm 1: Our approach for solving (1)

Data: An image set $\mathcal{I}$ containing images of the same category

Result: Sets $\mathcal{O}$ and $\mathcal{K}$ containing segmentations and skeletons of images in $\mathcal{I}$

Initialization: $\forall I_i \in \mathcal{I}$, $O_i^{(0)}$ = Otsu thresholded saliency map and $K_i^{(0)} = \mathbf{ma}(O_i^{(0)})$;

Process: $\forall I_i \in \mathcal{I}$,

do

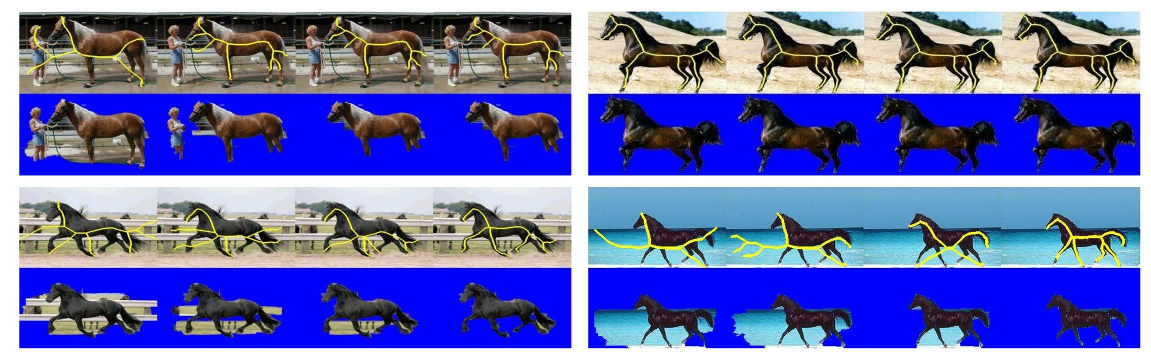
1) Obtain $O_i^{(t+1)}$ by solving (3) using [15] with $\mathcal{O}^{(t)}$ and $K_i^{(t)}$.

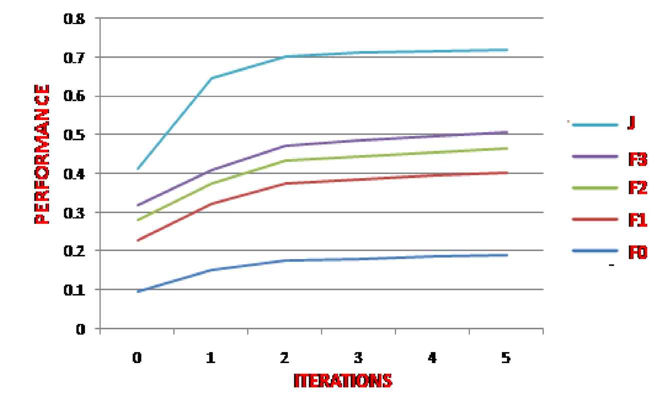
2) Obtain $K_i^{(t+1)}$ by solving (2) using [21] with $\mathcal{K}^{(t)}$ and $O_i^{(t+1)}$, $s.t.\ K_i^{(t+1)} \in \mathbf{ma}(O_i^{(t+1)})$.

while $(\lambda\psi_{pr}+\psi_{in}+\psi_{sm})^{(t+1)} \leq (\lambda\psi_{pr}+\psi_{in}+\psi_{sm})^{(t)}$;

$\mathcal{O} \leftarrow \mathcal{O}^{(t)}$ and $\mathcal{K} \leftarrow \mathcal{K}^{(t)}$

Experimental Results





Method	F^0	F^1	F^2	F^3	J
Ours$^{(0)}$	0.095	0.229	0.282	0.319	0.412
Ours (w/o ψ_{in})	0.168	0.337	0.391	0.434	0.649
Ours	**0.189**	**0.405**	**0.464**	**0.506**	**0.721**

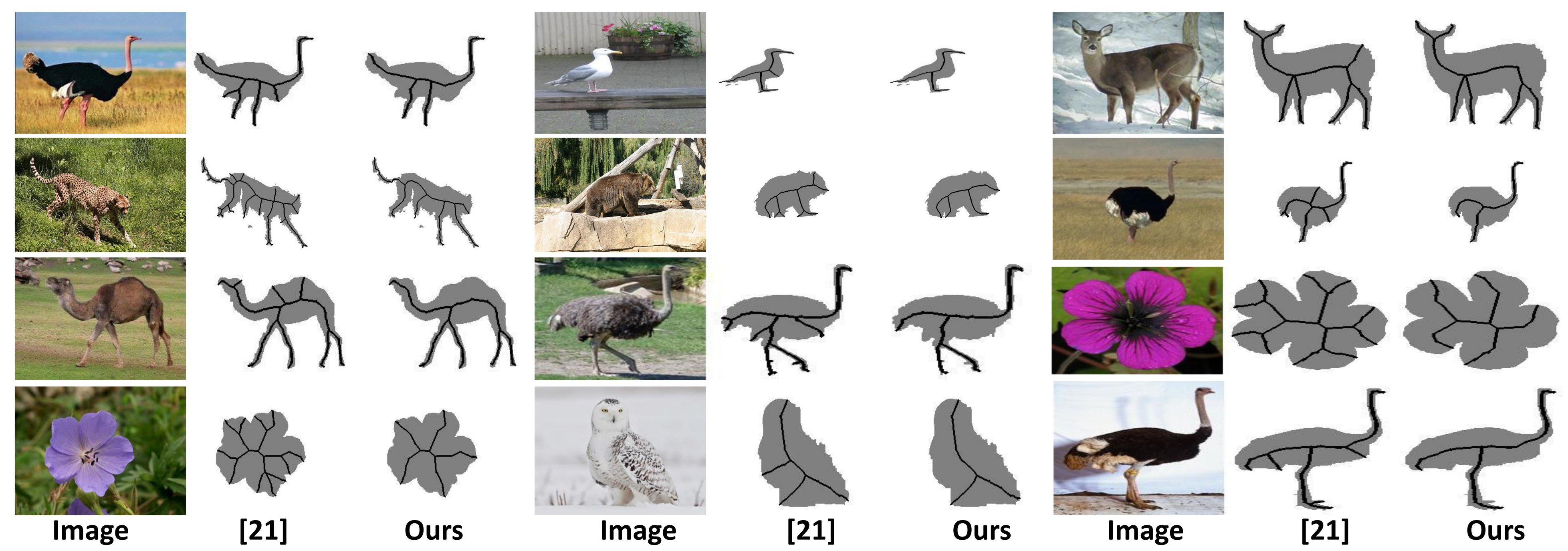
Methods		WH-SYMMAX	SK506
[9]	Traditional ML	0.174	0.218
[8]		0.223	0.252
[26]		0.334	0.226
[23]		0.103	-
[25]		0.365	0.392
[29]		0.402	-
Ours$^{(0)}$		0.322	0.261
Ours		0.530	0.483
Ours (S)		**0.594**	**0.523**

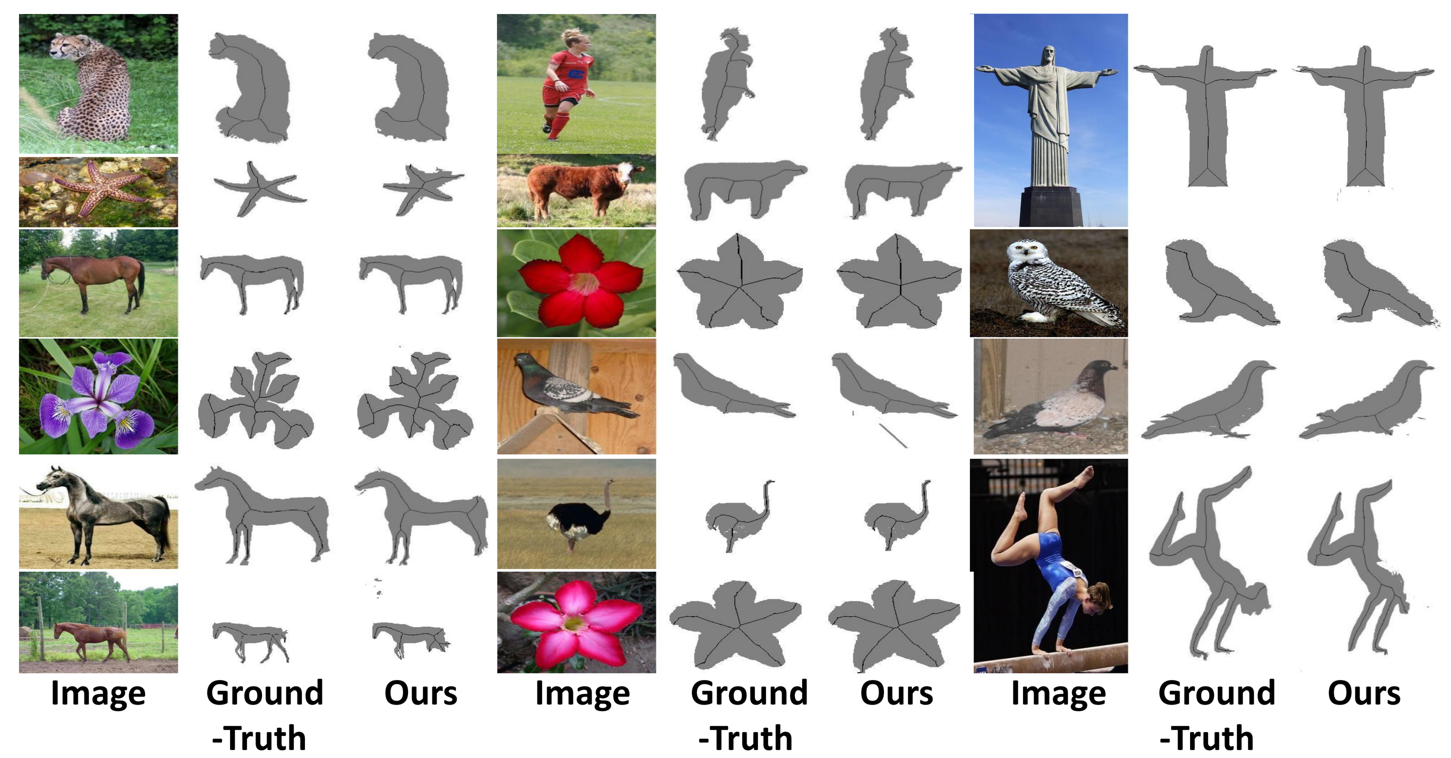
Smoothness Modification

[21] : small number of skeleton pixels

Ours: small numbered big skeleton branches

Our New Dataset: CO-SKEL





References:

[15] Grabcut: Interactive foreground extraction using iterated graph cuts, TOG'04.

[21] Skeleton pruning as trade-off between skeleton simplicity and reconstruction error, SCIS'13.

[8] Detecting curved symmetric parts using a deformable disc model, ICCV'13.

[9] Multiscale symmetric part detection and grouping, ICCV'09.

[23] Multiscale centerline detection by learning a scale-space distance transform, CVPR'14.

[25] Learning-based symmetry detection in natural images, ECCV' 12.

[26] Local symmetry detection in natural images using a particle filtering approach, TIP'14.

[29] Accurate centerline detection and line width estimation of thick lines using the radon transform, TIP'07