

Articulated Object Tracking by Rendering Consistent Appearance Parts

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Title piece by piece

Articulated Object **Tracking**
by Rendering Consistent Appearance Parts

Problem Context

- Want to estimate configuration of a target object

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Articulated Object Tracking

by Rendering Consistent Appearance Parts

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- Want to estimate configuration of a target object
- Flexible object model and configuration space

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Articulated Object Tracking
by **Rendering** Consistent Appearance Parts

Problem Context

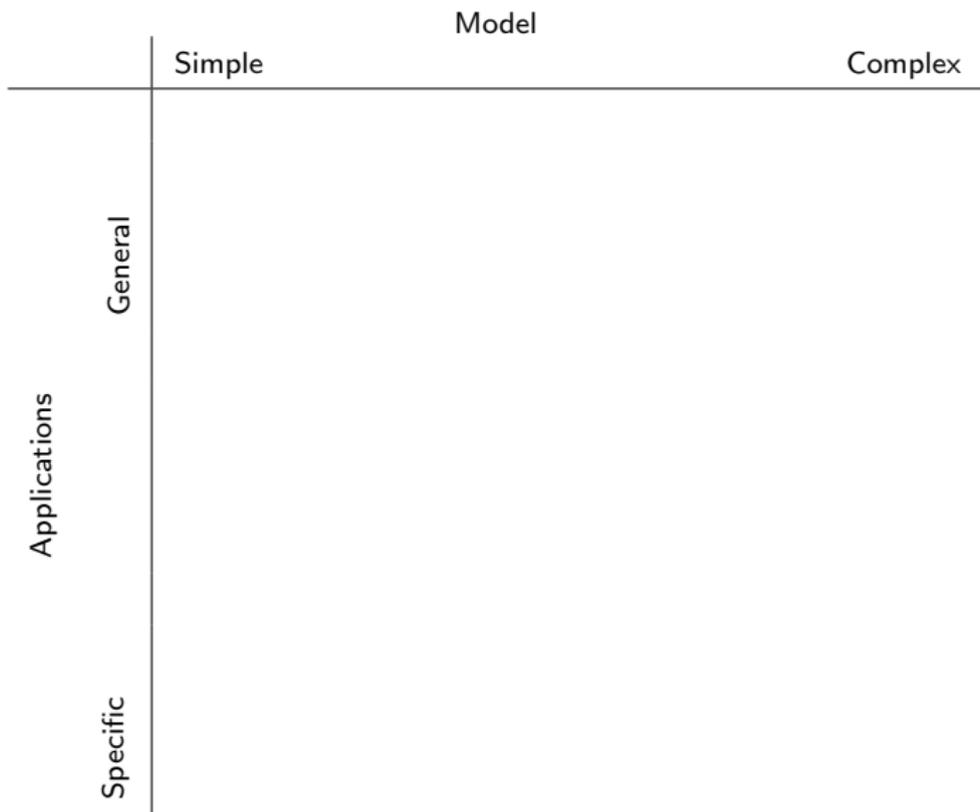
- Want to estimate configuration of a target object
- Flexible object model and configuration space
- Have geometric model of the target

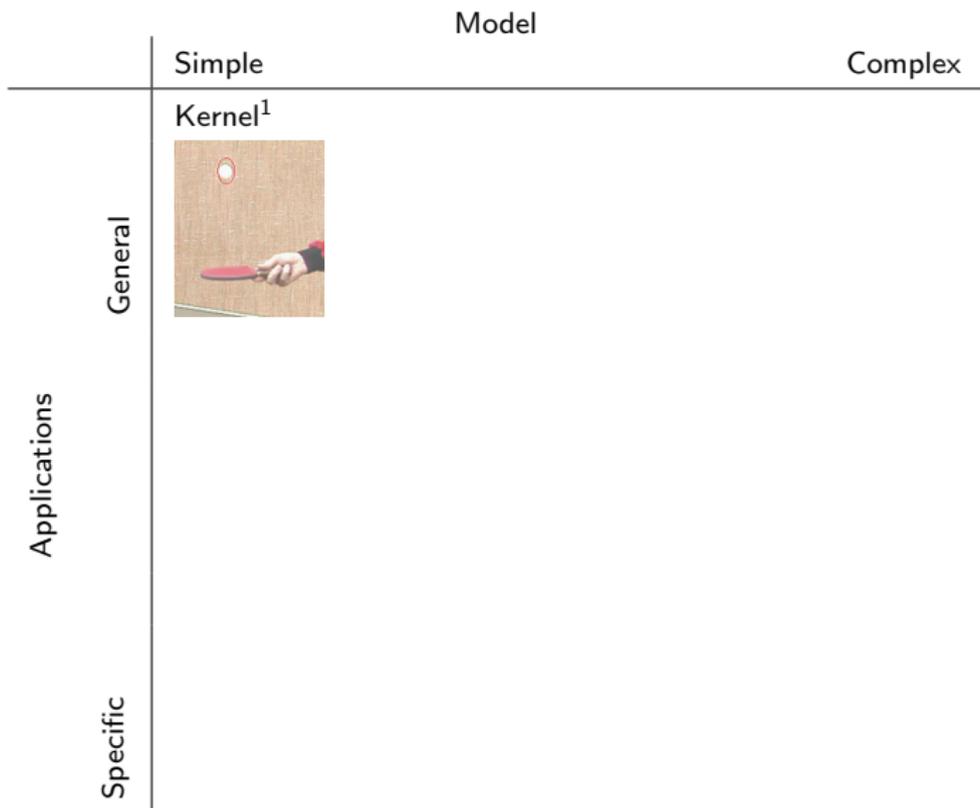
Title piece by piece

Articulated Object Tracking by Rendering **Consistent Appearance Parts**

Problem Context

- Want to estimate configuration of a target object
- Flexible object model and configuration space
- Have geometric model of the target
- Learn appearance model





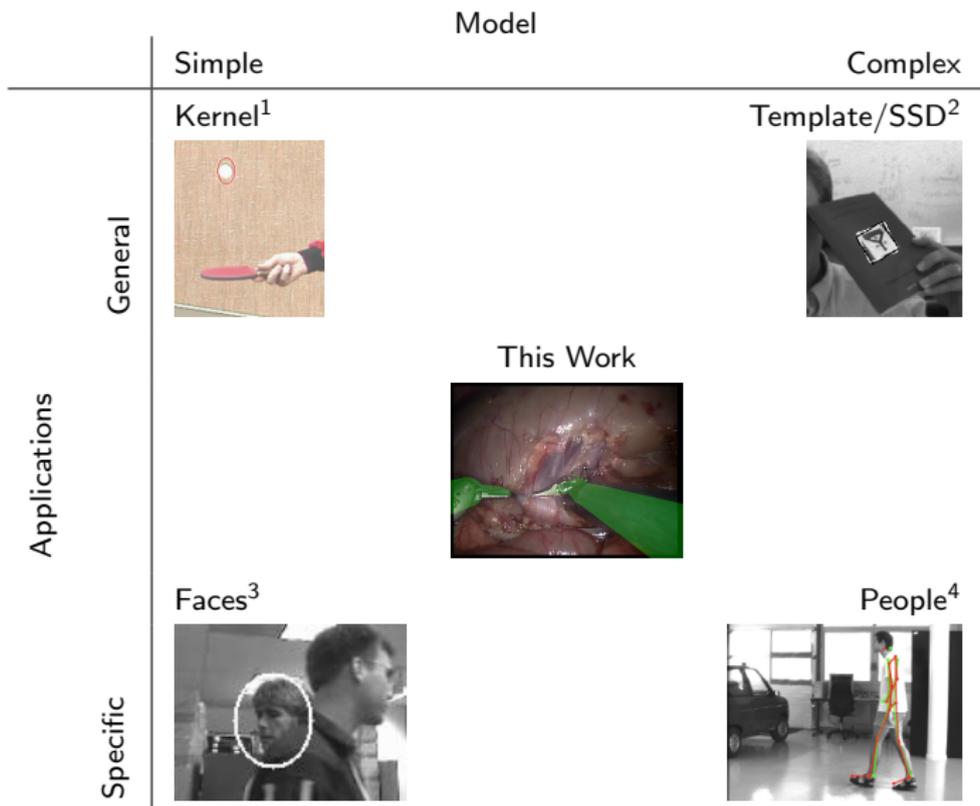
¹Comaniciu et al, PAMI '03.

		Model	
		Simple	Complex
Applications	General	Kernel ¹ 	Template/SSD ² 
	Specific		

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		Model	
		Simple	Complex
Applications	General	Kernel ¹ 	Template/SSD ² 
	Specific	Faces ³ 	People ⁴ 

¹Comaniciu et al, PAMI '03. ²Hager & Belhumeur, PAMI '98. ³ Birchfield, CVPR '98. ⁴, Z Lu et al, NIPS '07.



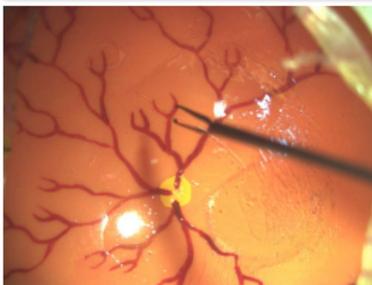
¹Comaniciu et al, PAMI '03. ²Hager & Belhumeur, PAMI '98. ³ Birchfield, CVPR '98. ⁴, Z Lu et al, NIPS '07.

General Approach

- Estimate appearance probability map
- Render object model in candidate configurations
- Maximize correlation b/w rendering and probability map

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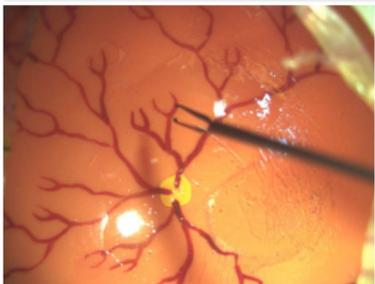


Retinal surgery

- Monoscopic
- 2D tracking of rigid tool mask
- 3 DOF

General Approach

- Estimate appearance probability map
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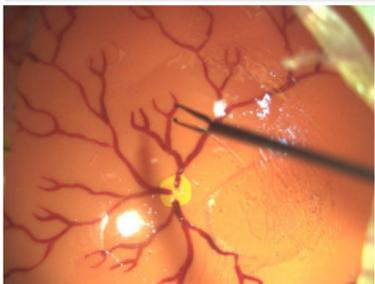


Da Vinci laparoscopic surgery

- Stereoscopic
- 3D tracking of 2 articulated tools
- 18 DOF

General Approach

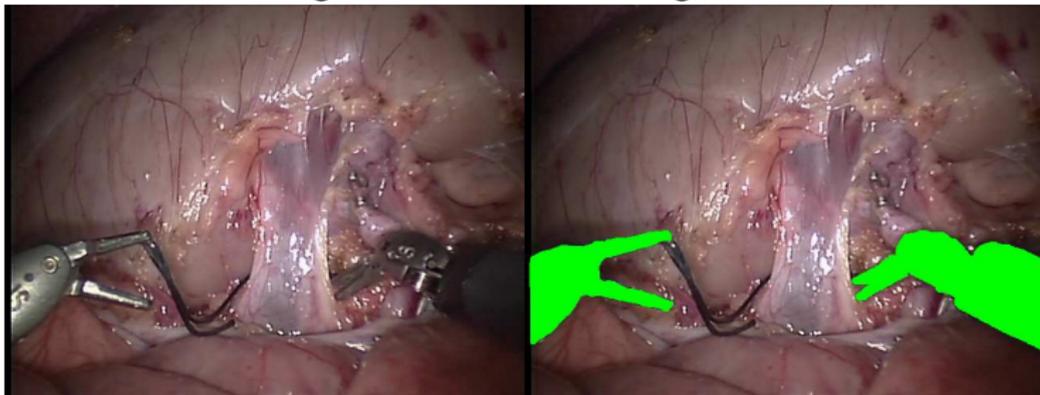
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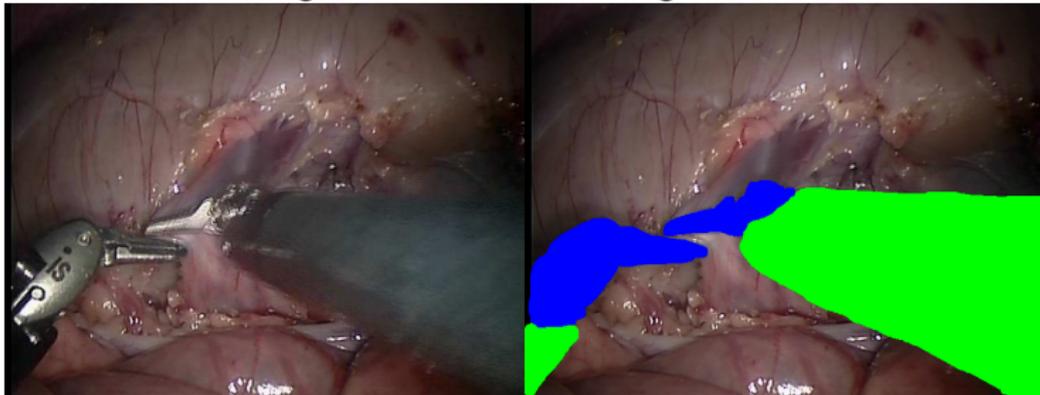
Human hand tracking

- Monoscopic
- 3D tracking of simplified hand model
- 18 DOF

Hand-segmentation with 1 foreground class



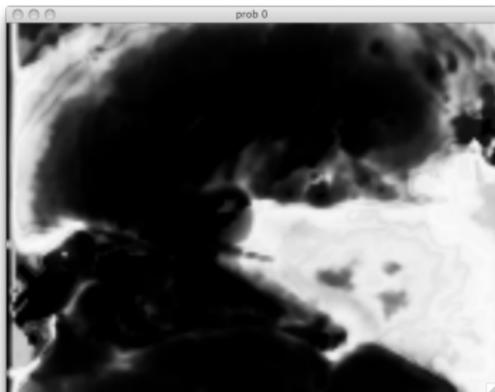
Hand-segmentation with 2 foreground classes



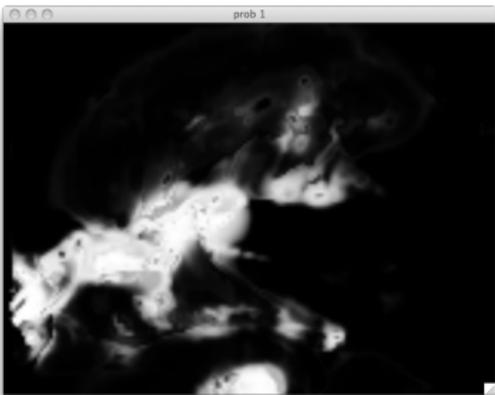
Input



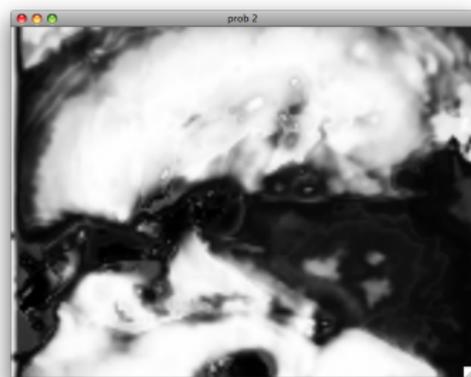
Tool shaft class



Tool tip class



Background class



Appearance Modeling Approach

- Separate object into consistent appearance parts and train
- Extract color and texture features
 - RGB and HSV blocks around current pixel
 - Haralick (GLCM) features: contrast, correlation, energy and homogeneity
- LDA to reduce dimensionality
- Fit GMM to each class

Gaussian Mixture Model (GMM) fit to each class, using LNKnet

Symbols

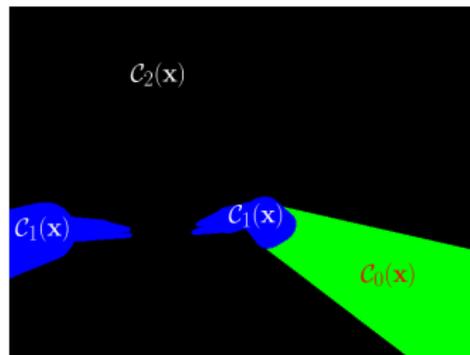
v	pixel feature vector
\mathcal{C}_j	class j
α	mixture weight
π	LDA projection
μ	mean
Σ	covariance

$$P(v | \mathcal{C}_j) = \sum_{i=1}^{\mathcal{C}^n} \alpha_i P(\pi v | \mu_i, \Sigma_i)$$

$$\text{with } P(\pi v | \mu_i, \Sigma_i) = \frac{1}{\sqrt{2\pi} |\Sigma_i|^{\frac{1}{2}}} e^{-\frac{1}{2}(\pi v - \mu_i)^T \Sigma_i^{-1} (\pi v - \mu_i)}$$

Symbols

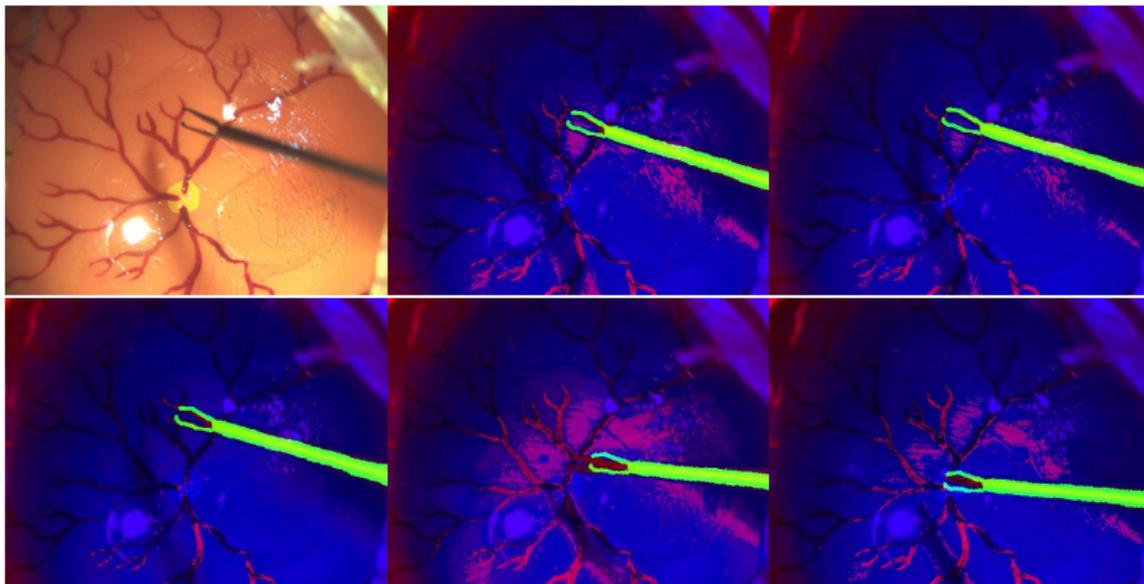
\mathbf{I}	Image
\mathbf{x}	Configuration
θ	Set of appearance classes
$\mathcal{C}_j(\mathbf{x})$	Pixels in class j

Visualization of $\theta(\mathbf{x})$

Want to maximize $P(\mathbf{I} | \mathbf{x}, \theta) = \prod_{\mathcal{C}_j \in \{\theta\}} \prod_{v \in \mathcal{C}_j(\mathbf{x})} P(v | \mathcal{C}_j)$

Use Nelder-Mead downhill simplex

For stereo, maximize $P(\mathbf{I}_1, \mathbf{I}_2 | \mathbf{x}, \theta)$ and $\mathcal{C}(\mathbf{x})$ may span both images.



Blue channel - greyscale of the original input

Red channel - foreground probability map

Green channel - rendering of best configuration estimate

Red channel - greyscale of the original input

Blue channel - foreground probability map

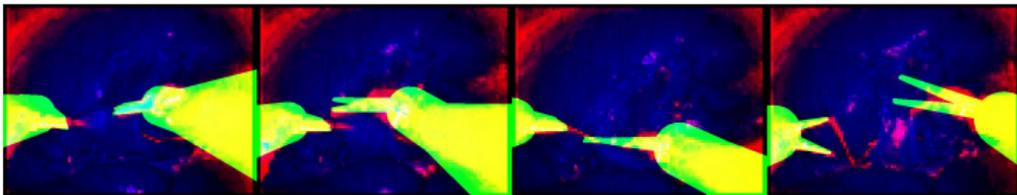
Green channel - rendering of best configuration estimate

Input



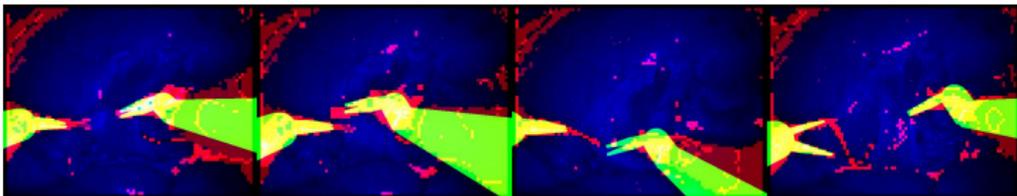
Blue channel - input greyscale, Red channel - foreground prob., Green channel - config. estimate

Single-class



Blue channel - input greyscale, Red channel - highest prob. class, Green channel - config. estimate

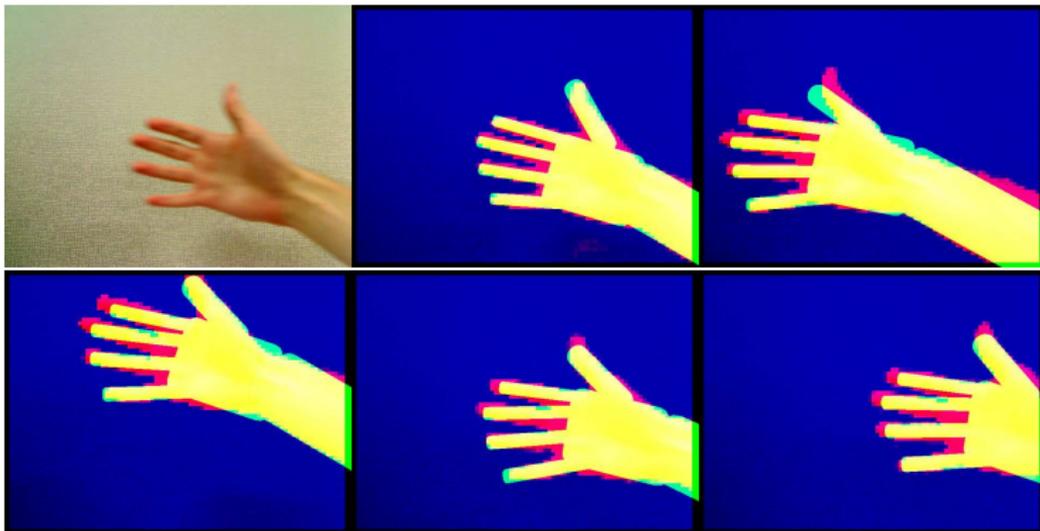
Multi-class



Blue channel - greyscale of the input

Red channel - value corresponding to highest probability class

Green channel - configuration estimate



Blue channel - greyscale of the original input

Red channel - foreground probability map

Green channel - rendering of best configuration estimate

Future Work

Potential extensions:

- Parallel implementation (GPU)
- Improved traversal of configuration space
- Adding edge information
- Dynamically updating appearance model

Acknowledgements

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Thank you for your attention.

Questions?