Qylur

Security Systems, Inc.

Object Separation in X-ray Image Sets

"SATISϕ"

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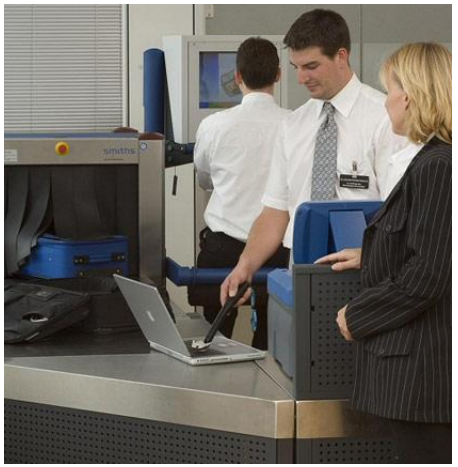
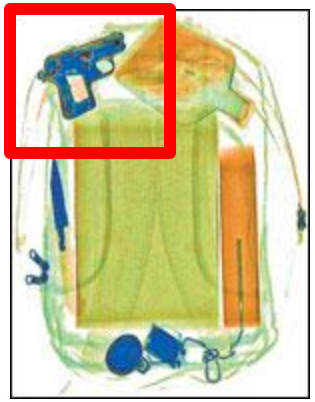
Motivation

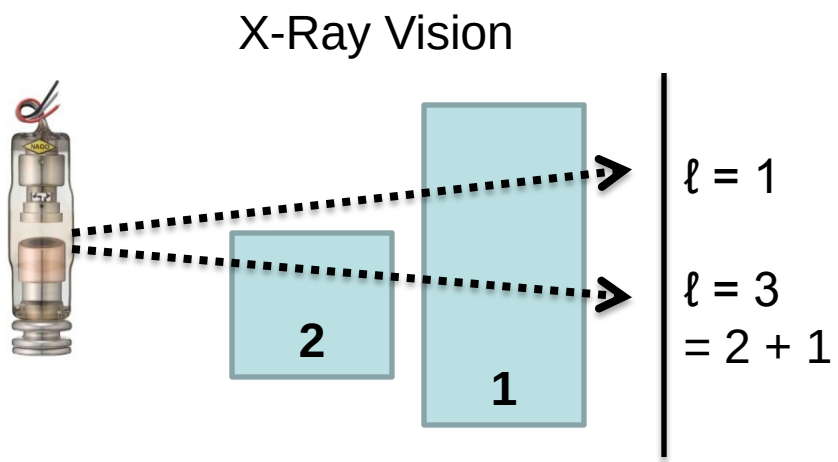
- Security checkpoints based on x-ray screening are increasingly important
- Our goal is to use computer vision tools to automate some of these procedures
- The challenge is to understand x-ray images automatically, taking the human out of the loop



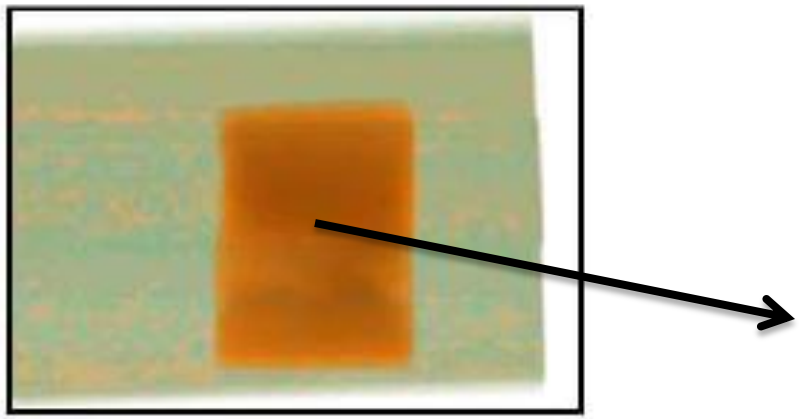
GUN



X-Ray Image Object Detection



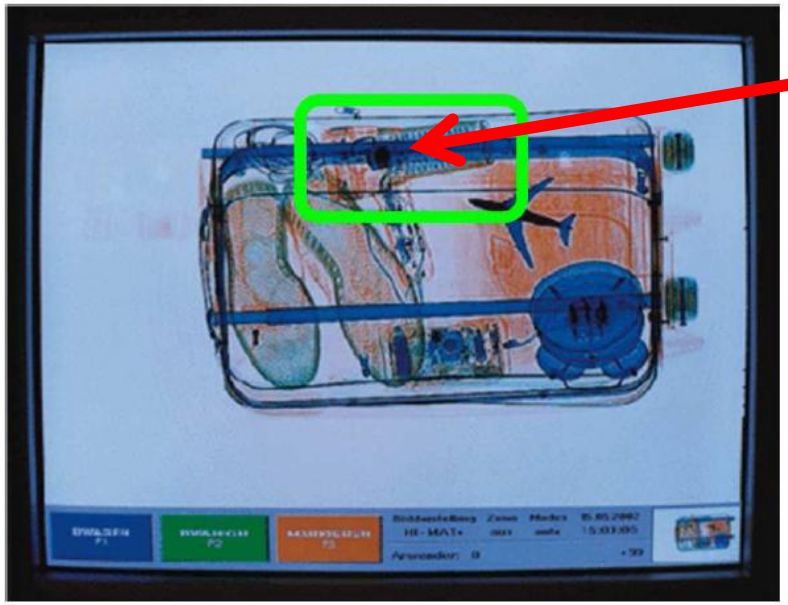
- We can “see-through” objects
- Measured attenuation is additive in log-space
- With dual energy techniques, we can determine the materials in the bag
- The types of materials help us detect objects of interest
  - Overlap makes this difficult



What are the material properties of this object?

Low-Level Vision: Segmentation

How do we “segment” an x-ray image?



Which “object” does **this pixel** belong to?

- ✓ The bag frame
- ✓ The flashlight

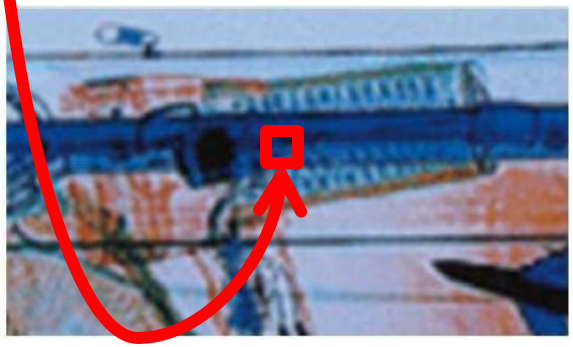
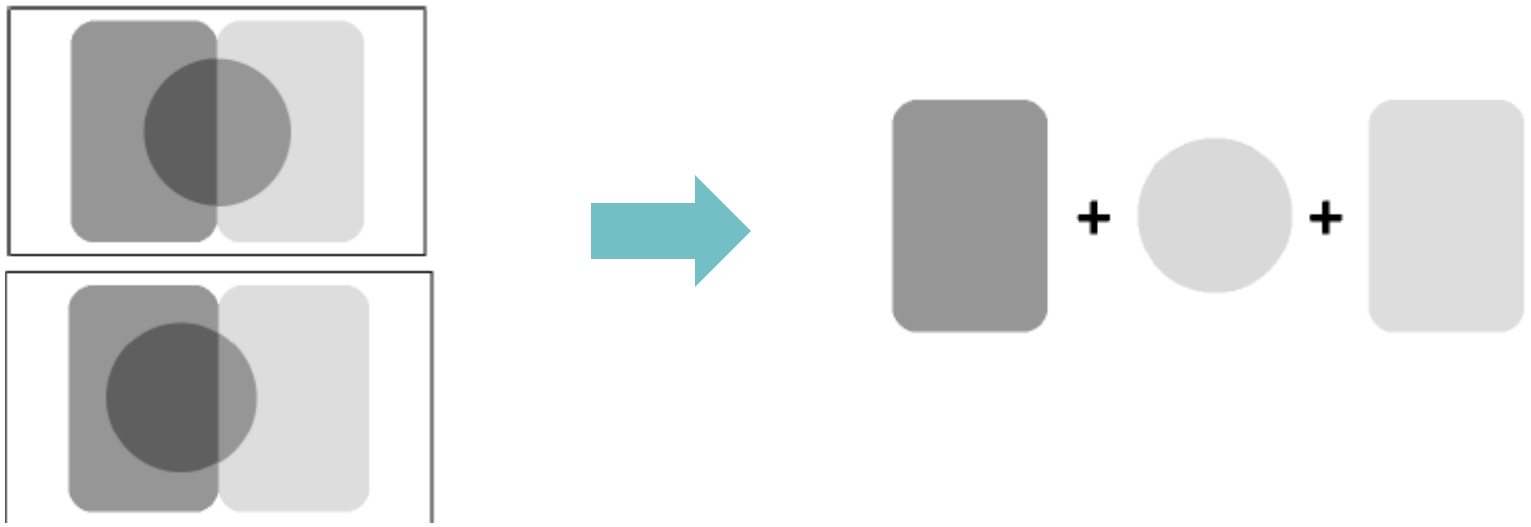


Image from: http://www.flughafen-duesseldorf.de/grafiken/cms/normalbild/Sicherheit4_mid.gif

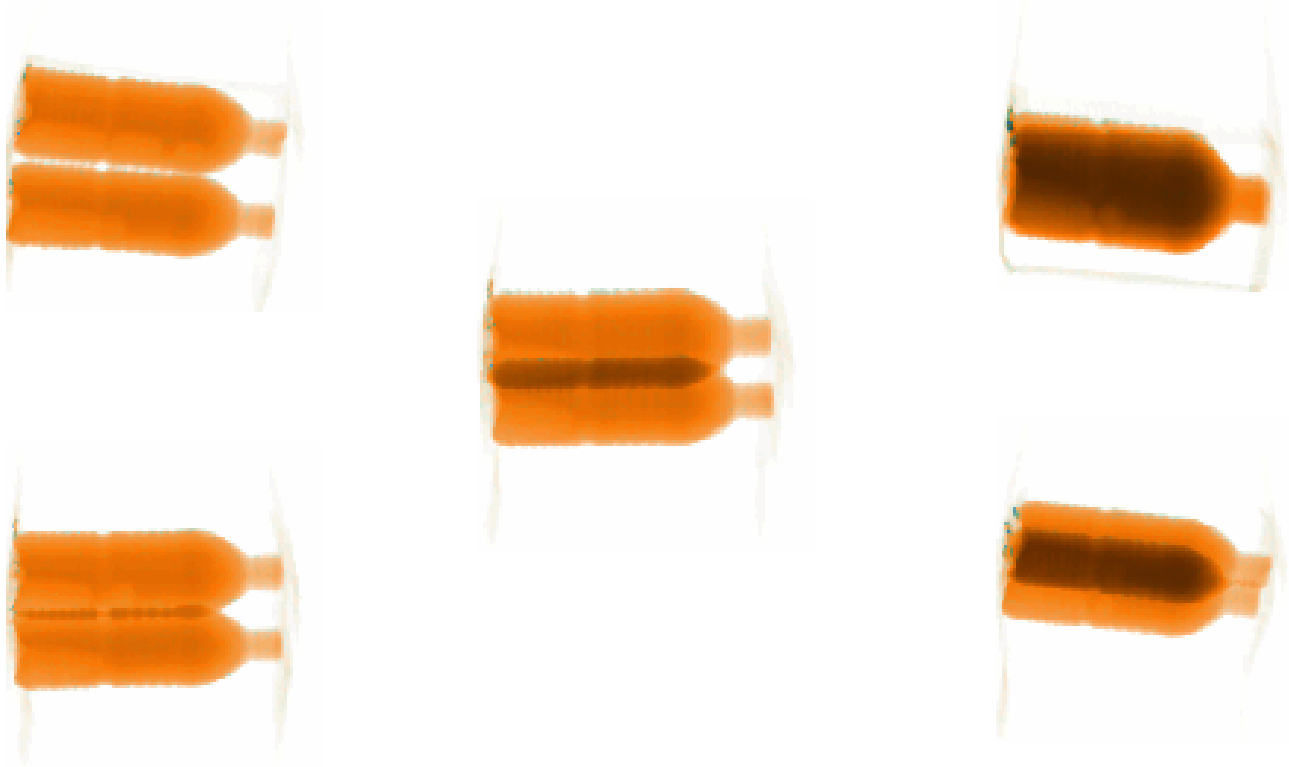
Low-Level Vision: Multiple Views

Single views are ambiguous.



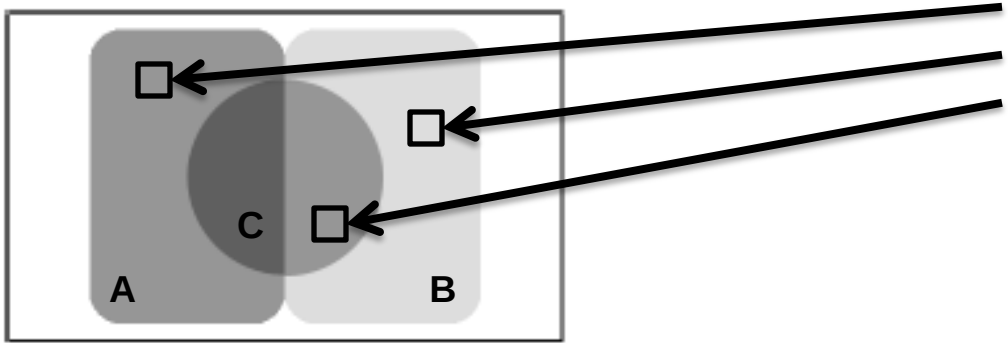
Multiple views can disambiguate the objects

Full Example



Problem Formulation

- Given a few views, decompose the image set into:
  - Composition matrix ***C***: indicates objects a pixel intersects



$$\begin{array}{c} \quad A \quad B \quad C \\ c_p = [1\ 0\ 0] \\ c_q = [0\ 1\ 0] \\ c_r = [0\ 1\ 1] \end{array}$$

  - Physical properties vector ***Φ***: the attenuation of each object

A	B	C

$$\Phi = [7.3\ 5.6\ 3.2];$$

*NOTE: We use superpixels for robustness

SATISϕ

- **S**mall-**A**ngle **T**ransmission **I**mage **S**eparation by ϕ

  - Probabilistic framework (MRF) for modeling the separation of objects (**C**,ϕ)

$$P(C,\phi) = \frac{1}{Z}\prod \psi(C,\phi)$$

  - Optimization procedure for finding a good separation from data

$$\left(C^*,\phi^*\right) = \arg\max_{C,\phi} P(C,\phi)$$

Data Model

- Sum of log-attenuation with Gaussian "noise"

$$\ell_{v,p} = \sum_{o} c_{v,p,o}\phi_{v,p,o} + \xi \quad \Rightarrow \quad \ell_{v,p} = \mathrm{N}\left(c_{v,p}^{T}\phi_{v,p}, \sigma_{\ell}^{2}\right)$$

Sum of objects this pixel intersects

Noise

$$\psi_{\ell}\left(\ell_{v,p}, c_{v,p}; \phi_{v,p}\right) = \mathrm{N}\left(\ell_{v,p}; c_{v,p}^{T}\phi_{v,p}, \sigma_{\ell}^{2}\right)$$

v = view index
p = pixel index
o = object index

- But this is under-constrained
  - We need additional "priors," based on intuitive and approximate assumptions

Assumptions

- Homogeneity
  - Objects are made up of a consistent material
- Smoothness
  - Neighboring pixels likely belong to same object(s)
- Small Angles (between views)
  - Constant Thickness
    - Thickness changes with cosθ
  - Area preservation
    - Projected area of object is similar between views
- All of these assumptions are reasonable for our data

SatisΦ MRF

APPEARANCE

$$P(c;\phi) = \frac{1}{Z}\prod_{v,p}\psi_{\ell}\left(\ell_{v,p}, c_{v,p};\phi\right)$$

$$\prod_{v,o,(p,q)}\psi_{S}\left(c_{v,p,o}, c_{v,q,o}\right)\prod_{v,w,o}\psi_{A}\left(c_{v,o}, c_{w,o}\right)$$

SMOOTHNESS

AREA PRESERVATION

Goal: MAP Decomposition

$$\left(c^*, \phi^*\right) = \arg\max_{c,\phi} P\left(c, \phi\right)$$

Overview of Algorithm:

Initialize $\boldsymbol{\Phi}$

Graph-based segmentation
[Felzenszwalb & Huttenlocher, IJCV 2004]

REPEAT until convergence

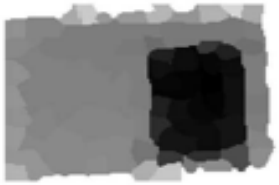
- Optimize $\boldsymbol{c}$ with fixed $\boldsymbol{\Phi}$
- Optimize $\boldsymbol{\Phi}$ with fixed $\boldsymbol{c}$
- (Global) joint optimization of $(\boldsymbol{\Phi}, \boldsymbol{c})$

QP Relaxation + Rounding
[Ravikumar & Lafferty, ICML 2006]
Least Squares
\ Operator in Matlab

Joint Optimization of **C** + ***Φ***

- "Global Moves"
  - ❑ Full Splits
  - ❑ Partial Splits
  - ❑ Merges
- Greedy hill-climbing with global moves

Data:



View #1

Current Separation:

Object #1 $\phi_i = 2$ Object #2 $\phi_i = 1$

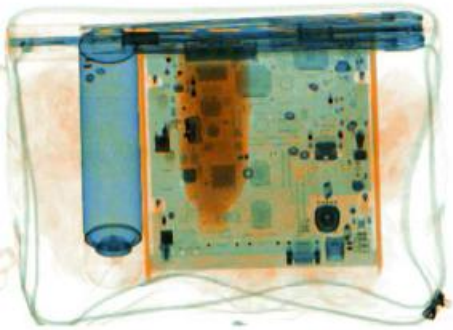
We want a "merge"

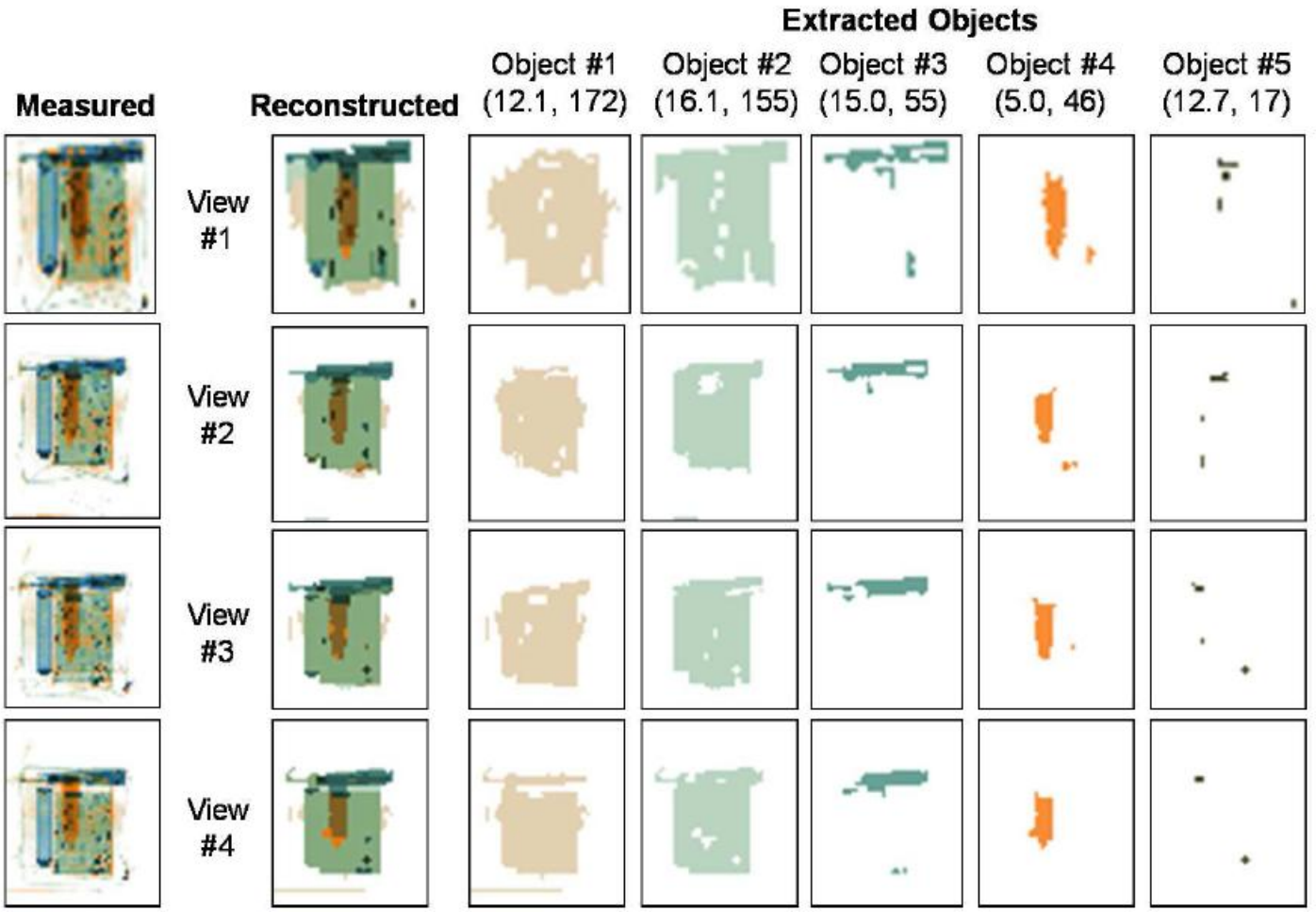
Improved Separation:

Object #1 $\phi_i = 1$ Object #2 $\phi_i = 1$

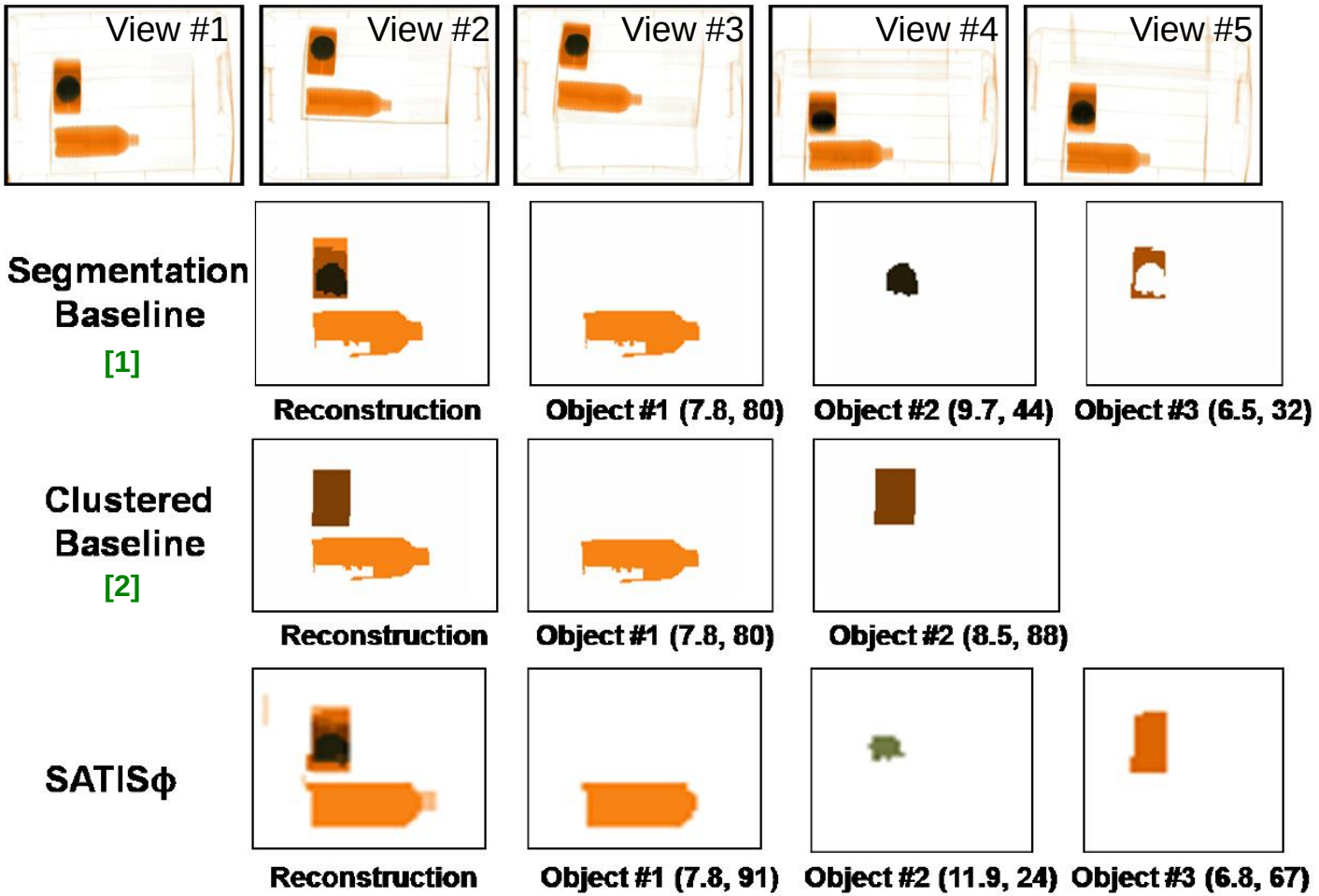
✓ Smoother

Example Result





Comparison to Baselines



[1] Felzenszwalb & Huttenlocher. IJCV 2004.

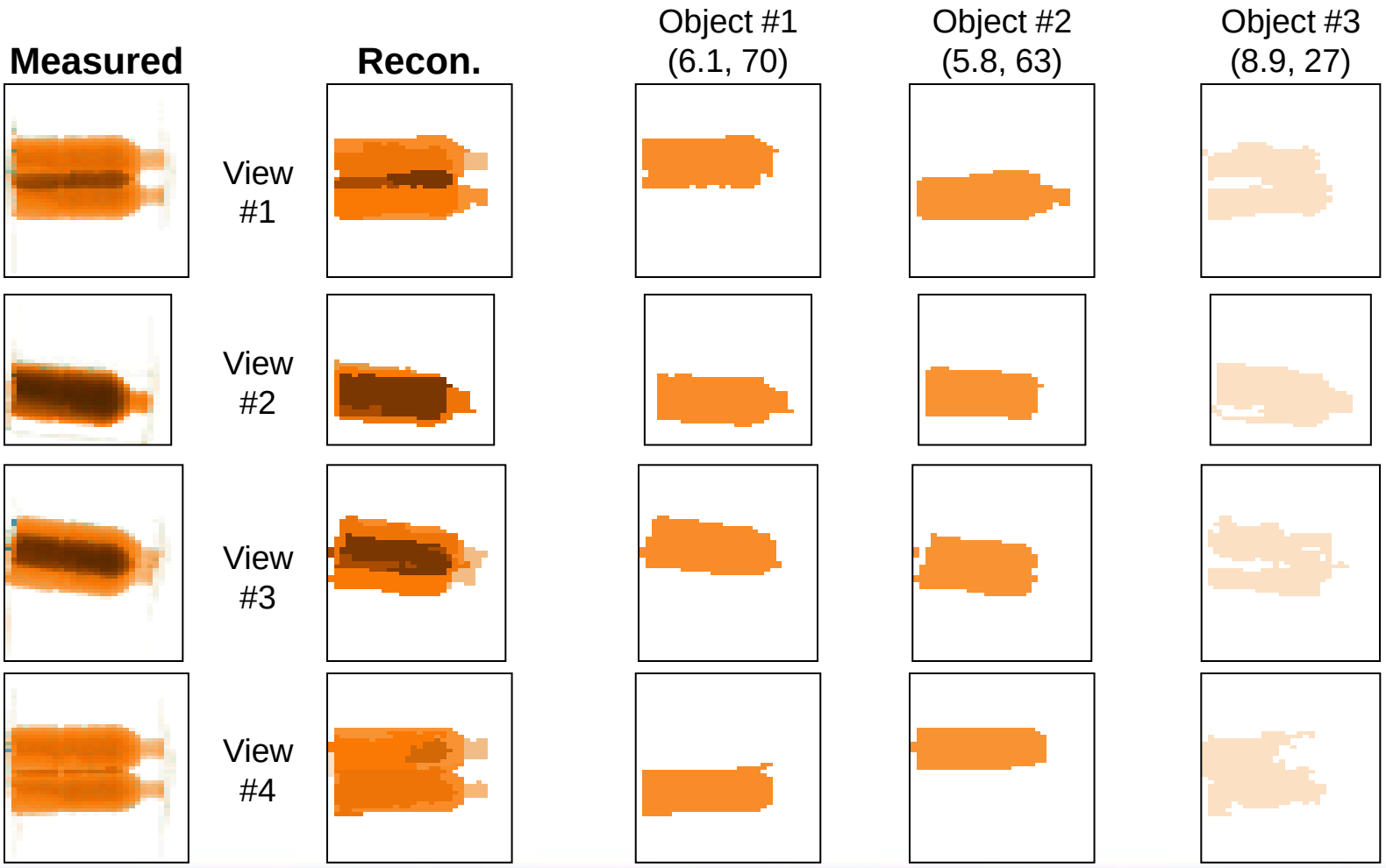
[2] Pelleg & Moore, ICML 2000.

Quantitative Comparison

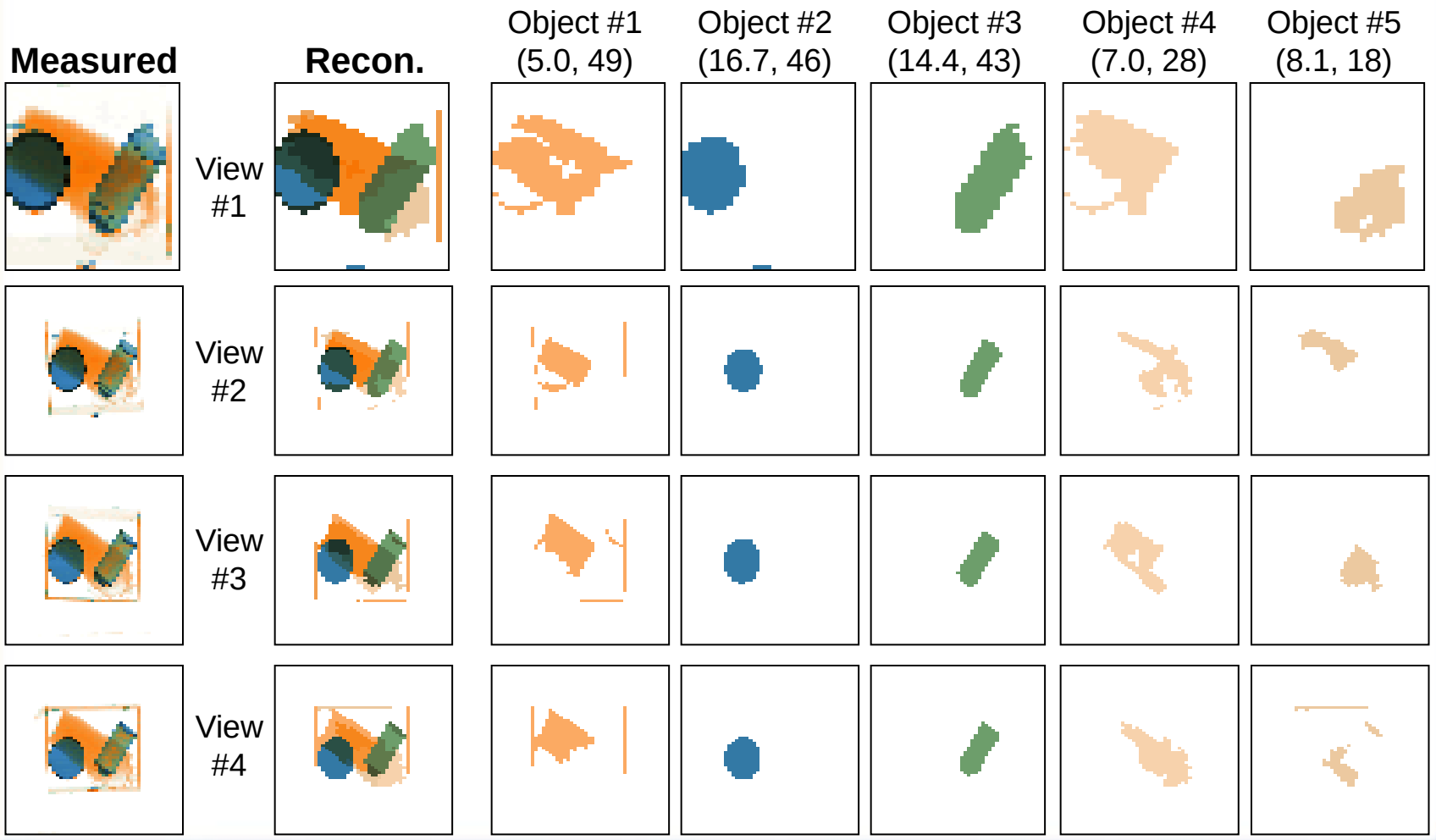
- Objects “matched” to manually annotated (true) objects by maximum overlap
- Determined error in material estimates for matched objects

	SATISφ	Segmentation	Clustered Segmentation
RMS Mass	**0.66**	1.15	1.32
RMS Atomic Number	**1.55**	2.52	2.71
Matched Objects	**33**	31	29
Missed Objects	**33**	35	37
Excess Objects	22	61	**12**

Results – Water Bottles



Results – Three Objects

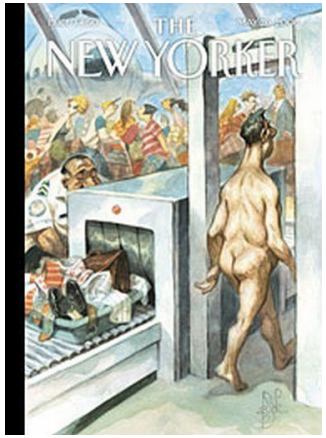


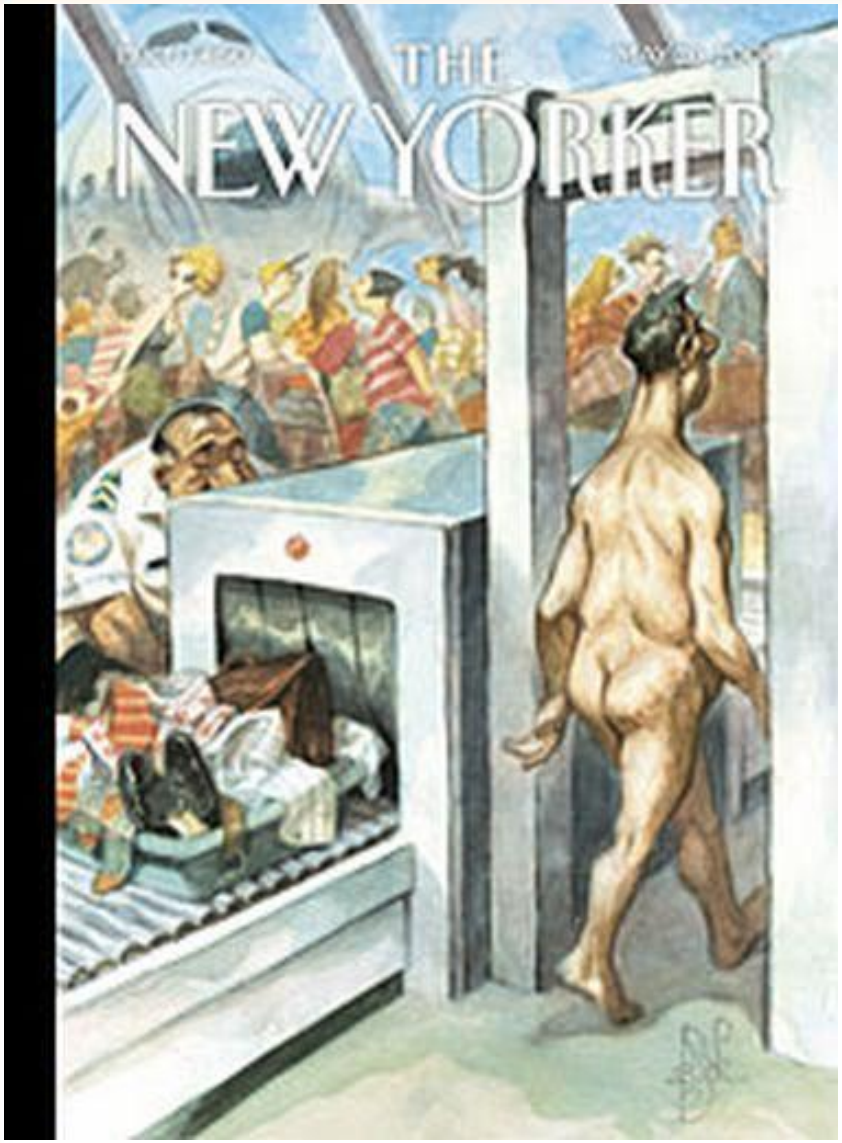
Summary

- Objects in x-ray images require layered separation, rather than segmentation
- We formulate the problem as an MRF, and solve it with coordinate ascent plus global steps
- The resulting separation allows for better estimates of the object properties

Conclusion

- X-ray vision…
  - shares much in common with visible spectrum vision
  - leads to exciting new challenges and applications in the real world
- Imagine if one day all of our security is handled efficiently and automatically…





THANKS!

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