Stochastic geometry

for

automatic object detection and tracking

in

remotely sensed image sequences

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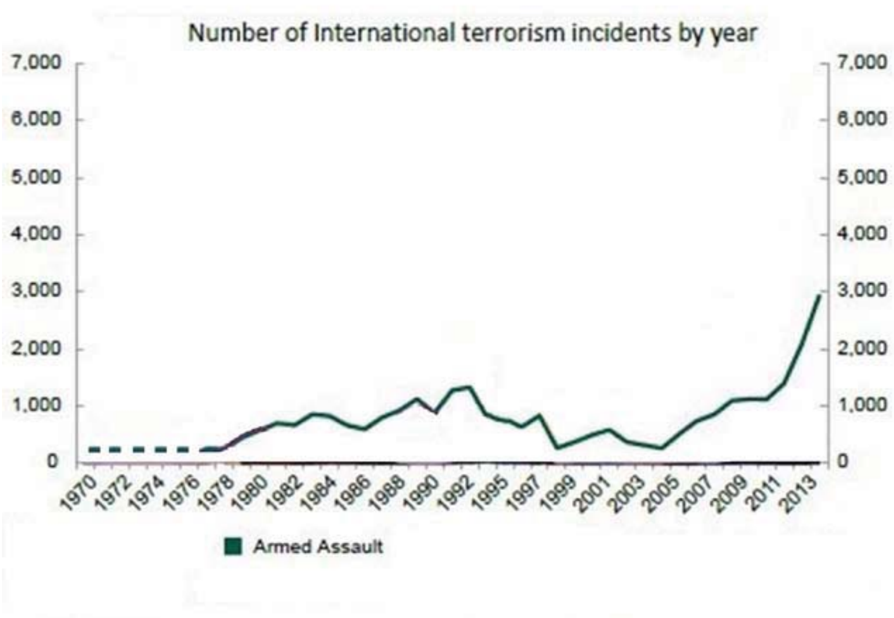
This work has been done in collaboration with dr. Josiane ZERUBIA from INRIA and dr. Mathias Ortner from Airbus Defense and Space, France

DEMO

Surveillance – now more than ever

Human benefits



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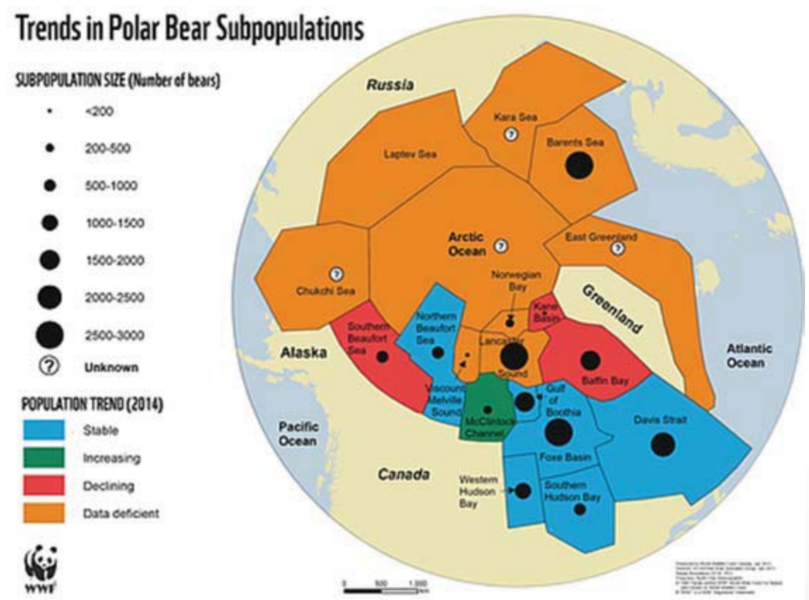
Wildlife benefits



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Optical airborne and space-borne systems

- UAVs (unmanned aerial vehicles)
  - Sub-meter ground sampling resolution imagery
  - Unstable platform

- Low-orbit satellites
  - Sub-meter ground sampling resolution imagery
  - Stable platform
  - High-definition video of up to 90 seconds at 30 frames / second

- Geostationary satellites
  - 1km ground sampling resolution imagery
  - Low temporal frequency …

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Challenges

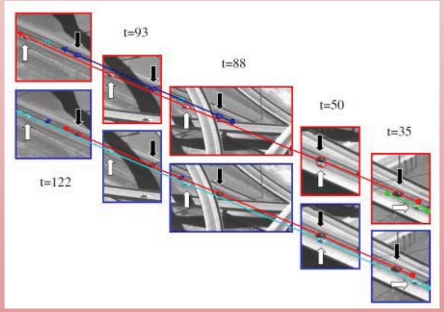
- Small object size
- Large number of objects
- Shadows
- Independent camera / object motion
- Time requirements

Multiple Object Tracking (MOT)

- **Goal**: Extract object trajectories throughout a video
- Two sub-problems
  - **Where are the possible targets?** - Detection of targets
  - **Which detection corresponds to each target?** - Solve the data association problem
- Two data-handling approaches
  - **Sequential** – iteratively analyze frames in temporal order
  - **Batch processing** – analyze the entire video at once
- Two main problem solving approaches
  - **Tracking by detection**
  - **Track before detect**

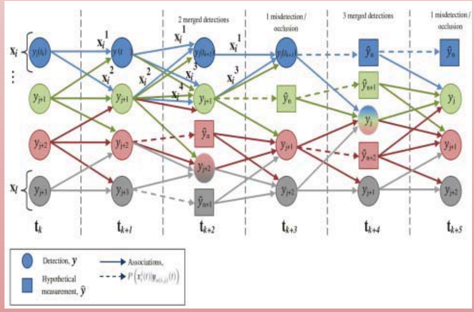
Data-association based methods

NN-app



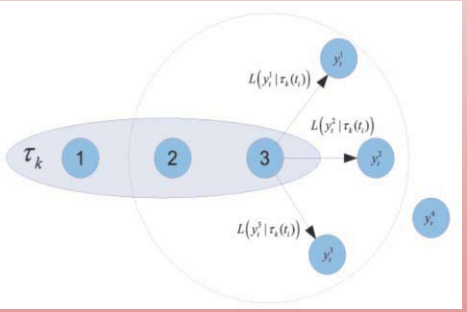
[Perera2006]

DD-MCMCDA



[Yu2008]

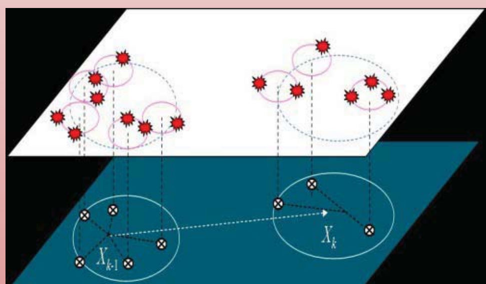
MHT



[Saleemi2013]

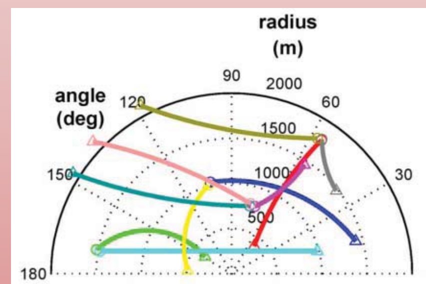
RFS-based methods

RFS



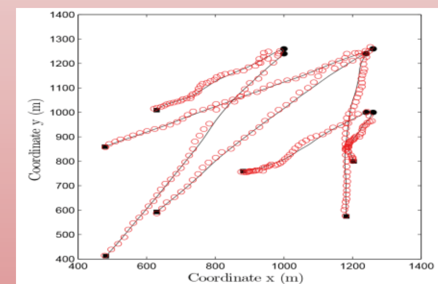
[Mahler2003]

PHD



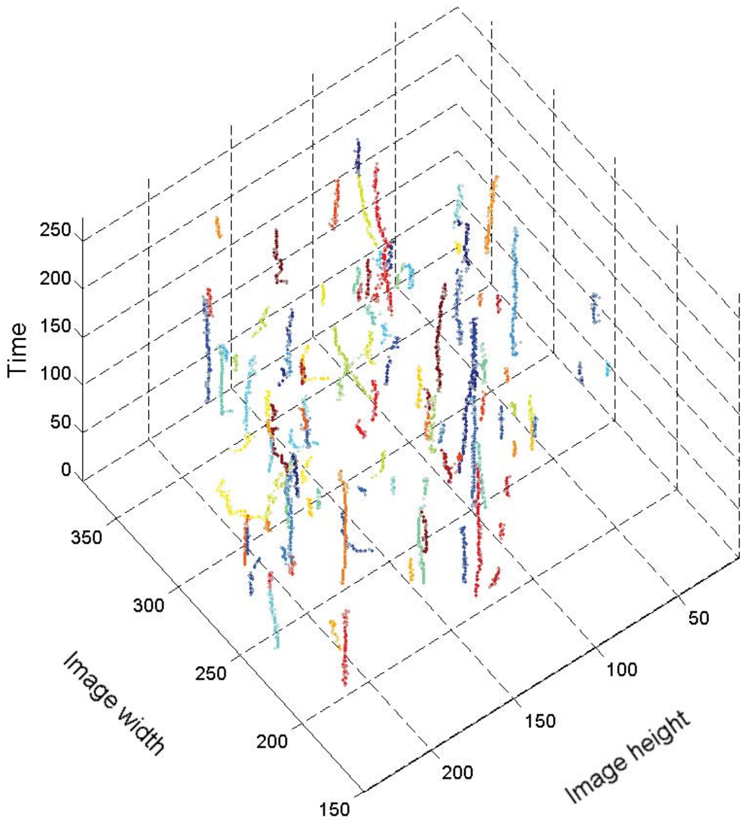
[Vo2005]
[Vo2006]
[Pace2011]

L-RFS / GLMB



[Vo2013]
[Vo2014]
[Papi2015]

Patterns and stochastic geometry



- Object tracking as a spatio-temporal marked point process
- How to model and simulate such a spatio-temporal point process?

Thesis at a glance

- Marked point process models for object detection and tracking
- Linear programming for automatic or semi-automatic parameter learning
- Model simulation using improved versions of RJMCMC

Overview

- Models
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Marked point process of ellipses

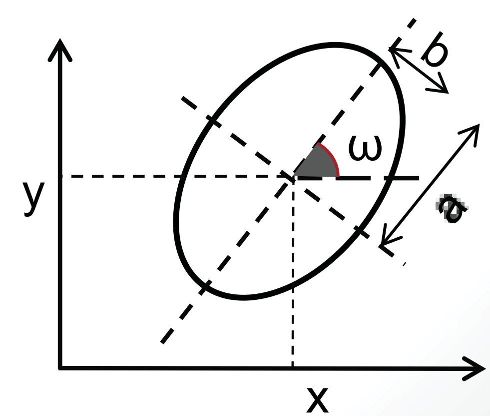
- Center of the ellipse is a point in the point process
- Marks:
  - Geometric marks: semi-major axis, semi-minor axis, orientation
  - Additional mark: label

$$W = K \times M$$

$$K = [0, I_{h_{max}}] \times [0, I_{w_{max}}] \times \{1, \cdots, T\}$$

$$M = [a_m, a_M] \times [b_m, b_M] \times (-\frac{\pi}{2}, \frac{\pi}{2}] \times [0, L]$$

$$u = (x_u, y_u, t, a, b, \omega, l)$$



Marked Point Process for Multiple Object Tracking

- Multiple object tracking problem
  - Searching for the most likely configuration $\mathbf{X}$ that fits the given image sequence $\mathbf{Y}$
- Solution
  - $\mathbf{X}$ is a realization of the Gibbs process given by:

$$f_\theta(X = \mathbf{X}|\mathbf{Y}) = \frac{1}{c(\theta|\mathbf{Y})} \exp^{-U_\theta(\mathbf{X},\mathbf{Y})} \tag{1}$$

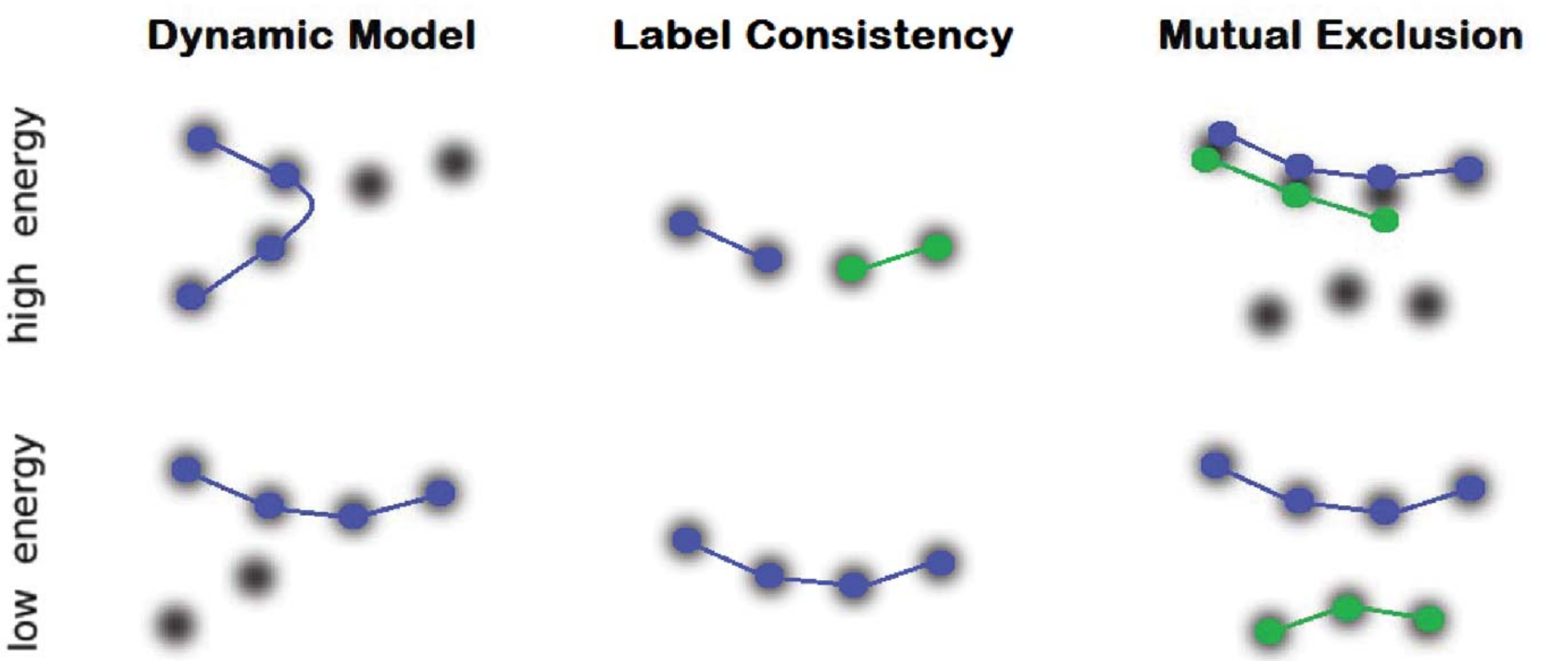
  - The most likely configuration is given by:

$$X \in arg \max_{\mathbf{X}\in\Omega} f_\theta(X = \mathbf{X}|\mathbf{Y}) = arg \min_{\mathbf{X}\in\Omega} [U_\theta(\mathbf{X},\mathbf{Y})]. \tag{2}$$

  - The process energy is composed of two energy terms:

$$U_\theta(\mathbf{X},\mathbf{Y}) = \underbrace{U^{ext}_{\theta_{ext}}(\mathbf{X},\mathbf{Y})}_{\text{External energy}} + \underbrace{U^{int}_{\theta_{int}}(\mathbf{X})}_{\text{Internal energy}}. \tag{3}$$

Internal energy



Constant velocity model | Long smooth trajectories | No overlapping objects

$$U^{int}_{\theta_{int}}(\mathbf{X}) = \gamma_{dyn} U^{int}_{dyn}(\mathbf{X}) + \gamma_{label} U^{int}_{label}(\mathbf{X}) + \gamma_o U^{int}_{overlap}(\mathbf{X})$$

External energy

Quality model

- Object evidence through frame differencing
- Contrast distance measure between interior and exterior of ellipse

$$U^{ext}_{\theta_{ext}}(\mathbf{X}|\mathbf{Y}) = \gamma_{ev}\mathcal{E}(u|\mathbf{Y}) + \gamma_{cnt}\sum_{u\in\mathbf{X}}\left(\mathcal{Q}\left(\frac{d_B(u,\mathcal{F}^\rho(u))}{d_0(\mathbf{Y})}\right)\right)$$

Statistical model

- Sliding window
- Two hypotheses:
  - H_0: The window covers only the background without any target being present
  - H_1: The window is placed in the center of a target
- Neyman-Pearson decision rule

$$U^{ext}_{\theta_{ext}}(\mathbf{X}|\mathbf{Y}) = \gamma_{stat}U^{ext}_{stat}(\mathbf{X}|\mathbf{Y})$$

Total energy

Quality model

External energy

$$U_\theta(\mathbf{X},\mathbf{Y}) = \boxed{\gamma_{ev}\mathcal{E}(u|\mathbf{Y}) + \gamma_{cnt}\sum_{u\in\mathbf{X}}\left(\mathcal{Q}\left(\frac{d_B(u,\mathcal{F}^\rho(u))}{d_0(\mathbf{Y})}\right)\right)} + \boxed{\gamma_{dyn}U_{dyn}^{int}(\mathbf{X}) + \gamma_{label}U_{label}^{int}(\mathbf{X}) + \gamma_o U_{overlap}^{int}(\mathbf{X})}$$

Internal energy

Statistical model

External energy

$$U_\theta(\mathbf{X},\mathbf{Y}) = \boxed{\gamma_{stat}U_{stat}^{ext}(\mathbf{X}|\mathbf{Y})} + \boxed{\gamma_{dyn}U_{dyn}^{int}(\mathbf{X}) + \gamma_{label}U_{label}^{int}(\mathbf{X}) + \gamma_o U_{overlap}^{int}(\mathbf{X})}$$

Internal energy

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Linear programming

- A linear program has the following form

(1) $$\text{Maximize: } \mathbf{a}^T\mathbf{C}$$

(2) $$\text{Subject to: } A^T\mathbf{C} \leq \mathbf{b}, \qquad \mathbf{C} \geq 0$$

Where:

- $\mathbf{a}^T$ – vector of coefficients
- $\mathbf{C}$ – parameter vector
- $A^T\mathbf{C} \leq \mathbf{b}$ – constraints

Objective function

- Quality model energy formulation

$$U_\theta(\mathbf{X},\mathbf{Y}) = \gamma_{ev}\ \mathcal{E}(u|\mathbf{Y}) + \gamma_{cnt}\sum_{u\in\mathbf{X}}\left(\mathcal{Q}\left(\frac{d_B(u,\mathcal{F}^\rho(u))}{d_0(\mathbf{Y})}\right)\right) +$$

$$\gamma_{dyn}\,U^{int}_{dyn}(\mathbf{X}) + \gamma_{label}\ U^{int}_{label}(\mathbf{X}) + \gamma_o\,U^{int}_{overlap}(\mathbf{X})$$

- Objective function

$$\mathbf{a} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \qquad \mathbf{c} = \begin{bmatrix} \gamma_{ev} \\ \gamma_{cnt} \\ \gamma_{dyn} \\ \gamma_{label} \\ \gamma_o \end{bmatrix}$$

Gathering constraints

- Only the ratio $\pi(\mathbf{X}')/\pi(\mathbf{X})$ is needs to be computed
- We can create inequalities of the form

$$\pi(\mathbf{X}')/\pi(\mathbf{X}) \geq 1 \tag{1}$$

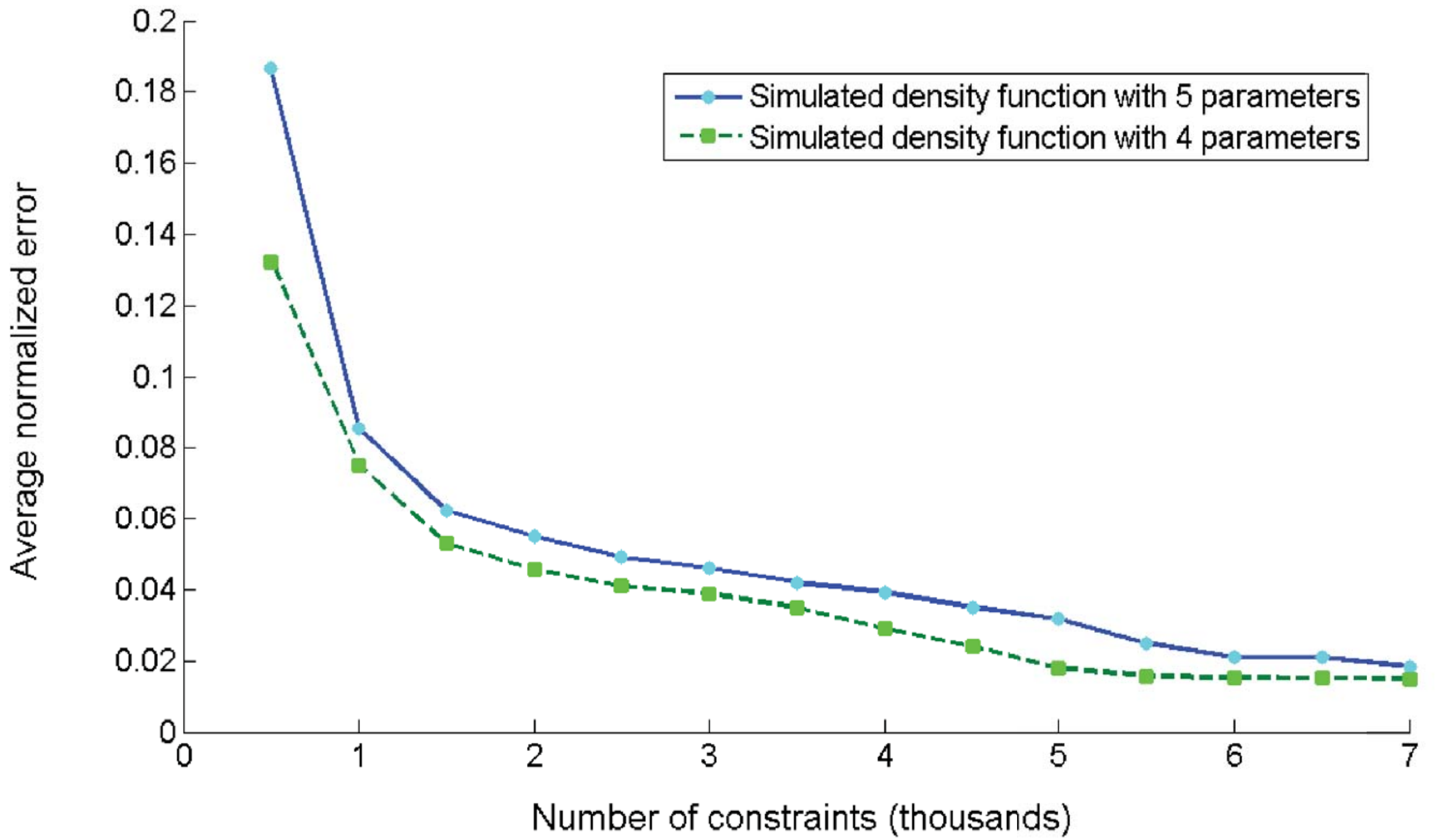
- If we have ground truth information

$$\frac{\pi(\mathbf{X}^*)}{\pi(\mathbf{X}_i)} \geq 1 \tag{2}$$

- Or more specifically the constraints can be written as

$$f(\mathbf{C}|\mathbf{X}^*) - f(\mathbf{C}|\mathbf{X}_i) \geq 0 \tag{3}$$

How many constraints?



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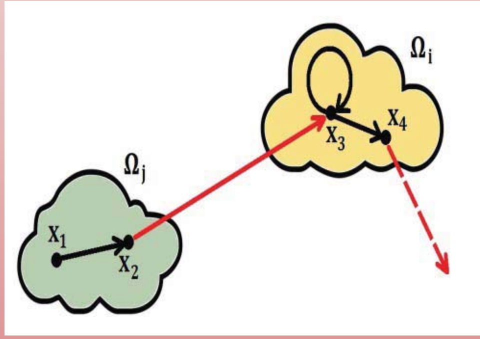
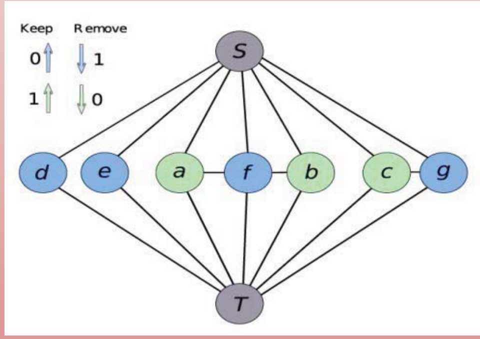
Related samplers

RJMCMC



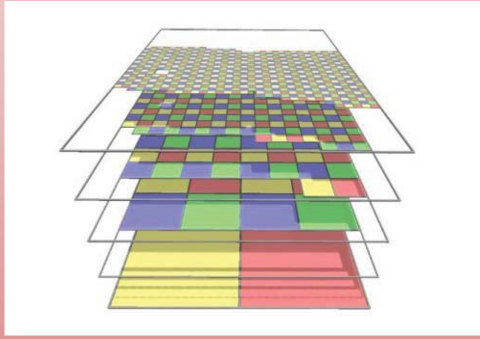
[Green1995]

MBD and MBC



[Descombes2009]
[Gamal2011]

P-RJMCMC



[Verdie2012]

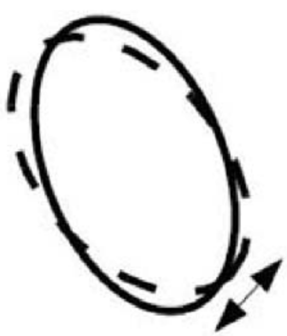
Classic RJMCMC

- Why?
  - Highly non-convex energy ⟶ MCMC
  - Unknown number of objects ⟶ RJ (reversible jump)
- Core idea
  - Create a Markov chain
  - Iteratively perturb the current state of the chain
  - Until convergence is reached

Standard perturbation kernels

- Birth and Death
  - Birth:
    - Add a new object to the configuration
  - Death:
    - Remove one object from the configuration
- Local transformations

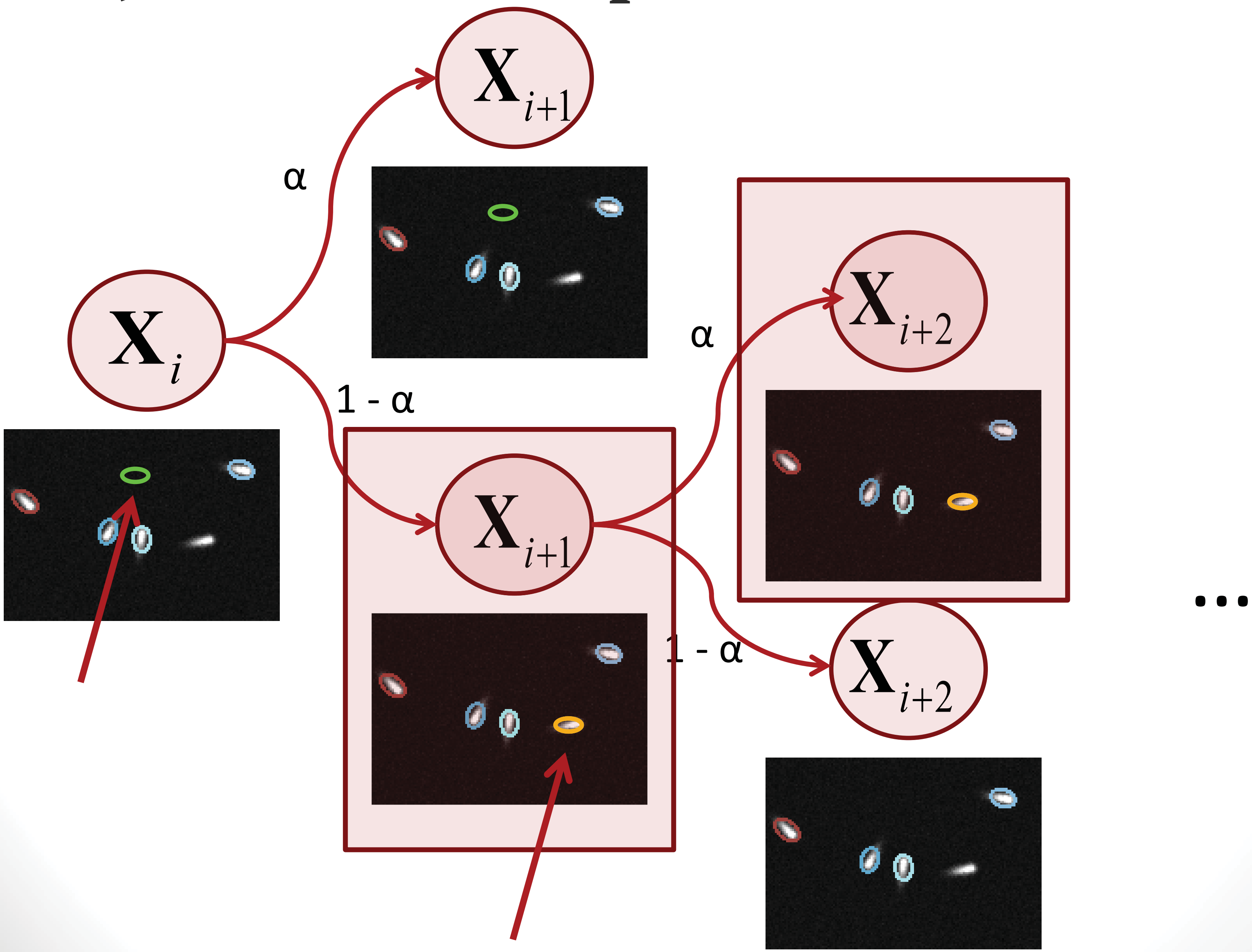
Rotation



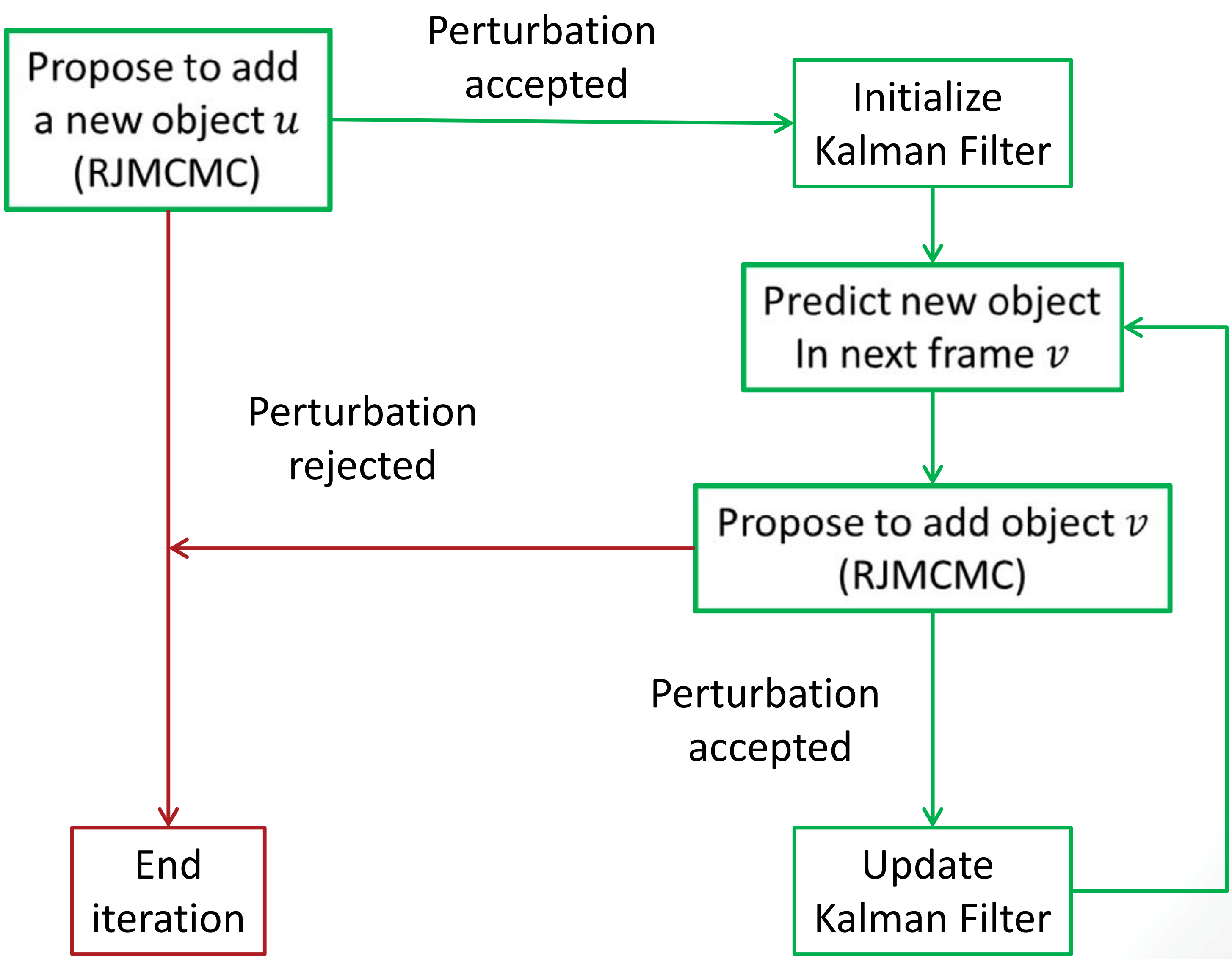
Translation

Scale

RJMCMC sampler

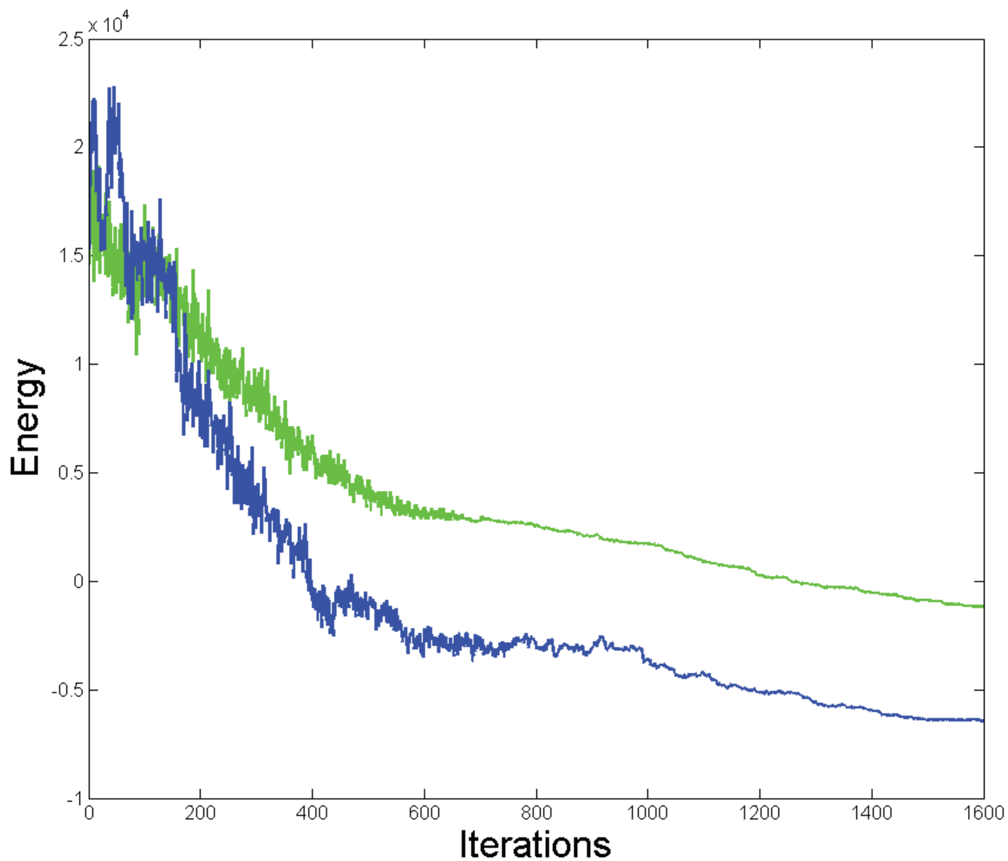


Adding Kalman-inspired births



Did time efficiency increase?

RJMCMC with Kalman like moves
converges much faster compared to the
standard RJMCMC



Experimental results
Satellite data
(4 objects / frame)

Kalman-inspired births reduce computation times!

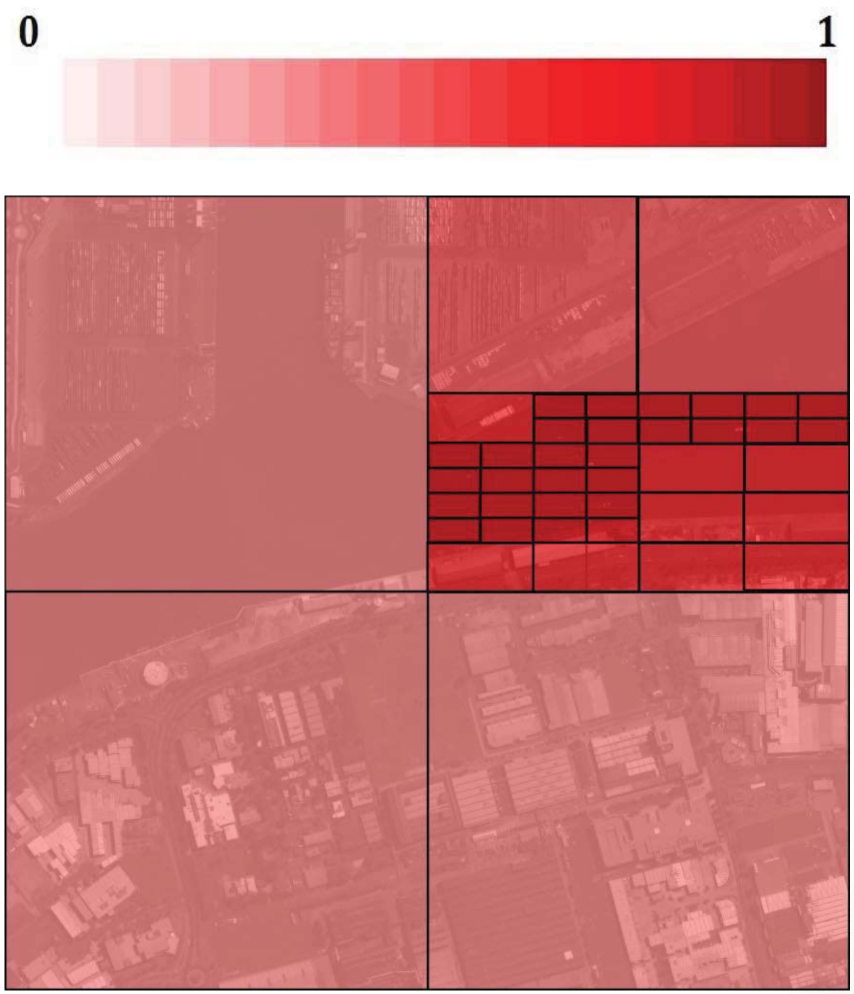
Parallel implementation of RJMCMC [Verdie2012]

- Data-driven space partitioning
- Locally conditional independent perturbations

Image with boats © Airbus D&S

Parallel implementation of RJMCMC

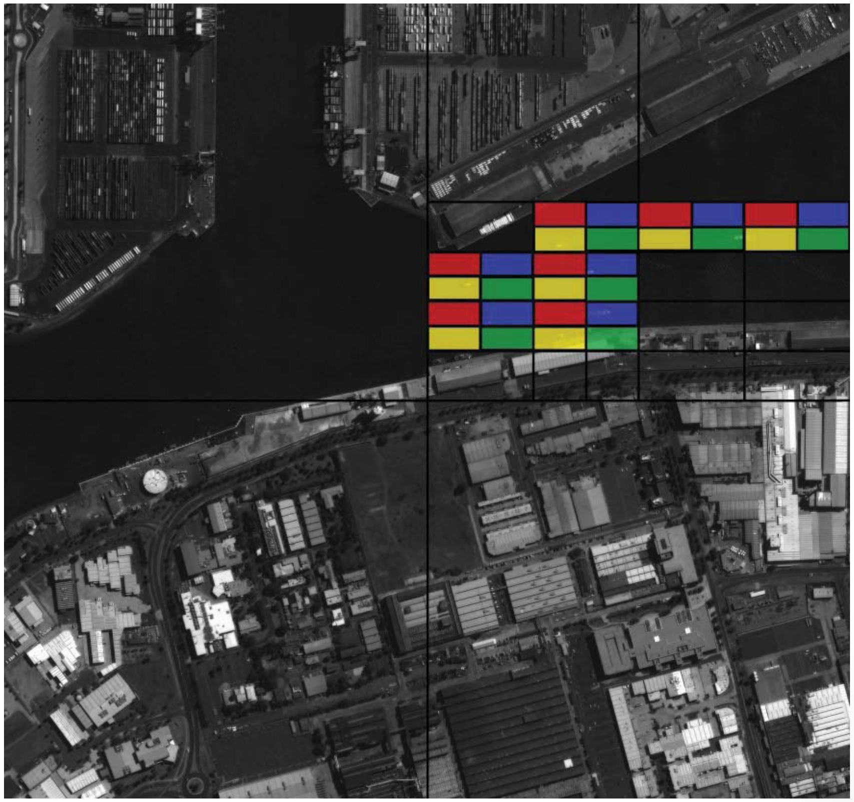
- Data-driven space partitioning
- Locally conditional independent perturbations



Probability that objects exist in each part of the image

Parallel implementation of RJMCMC

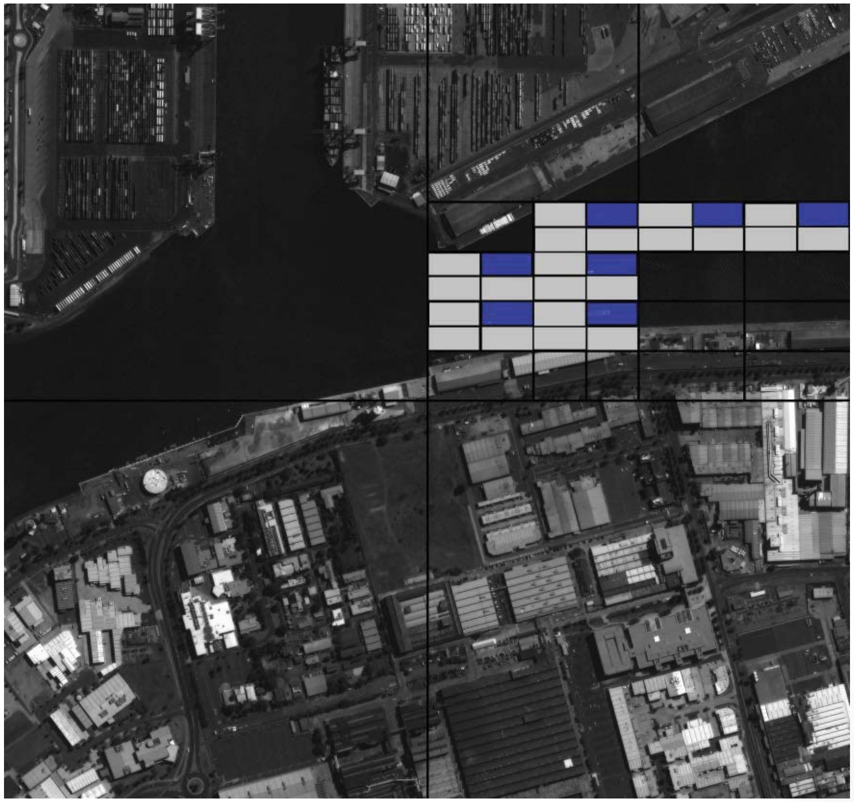
- Data-driven space partitioning
- Locally conditional independent perturbations



Color coding of quad-tree leafs

Parallel perturbations [Verdie2012]

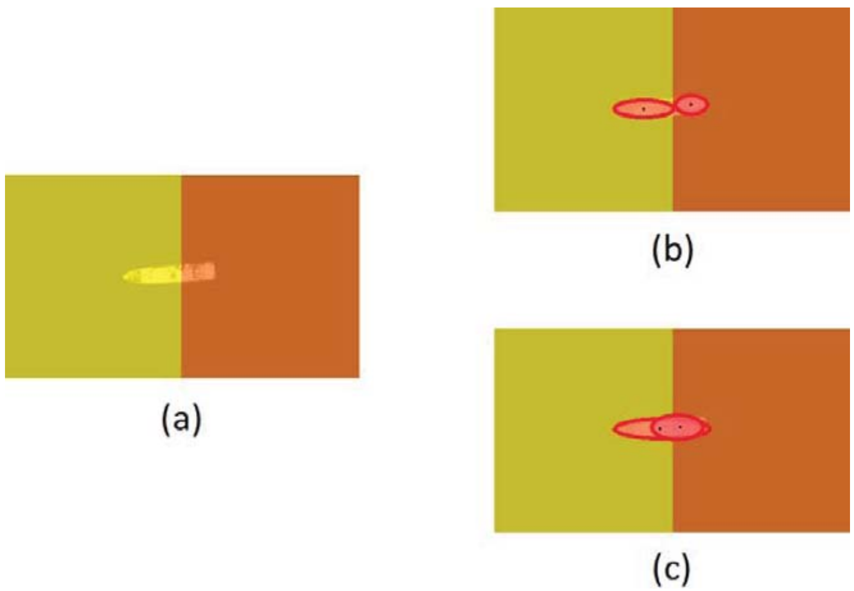
- A color is randomly chosen
- Perturbations are performed in all cells of the chosen color in parallel



Color blue is randomly chosen

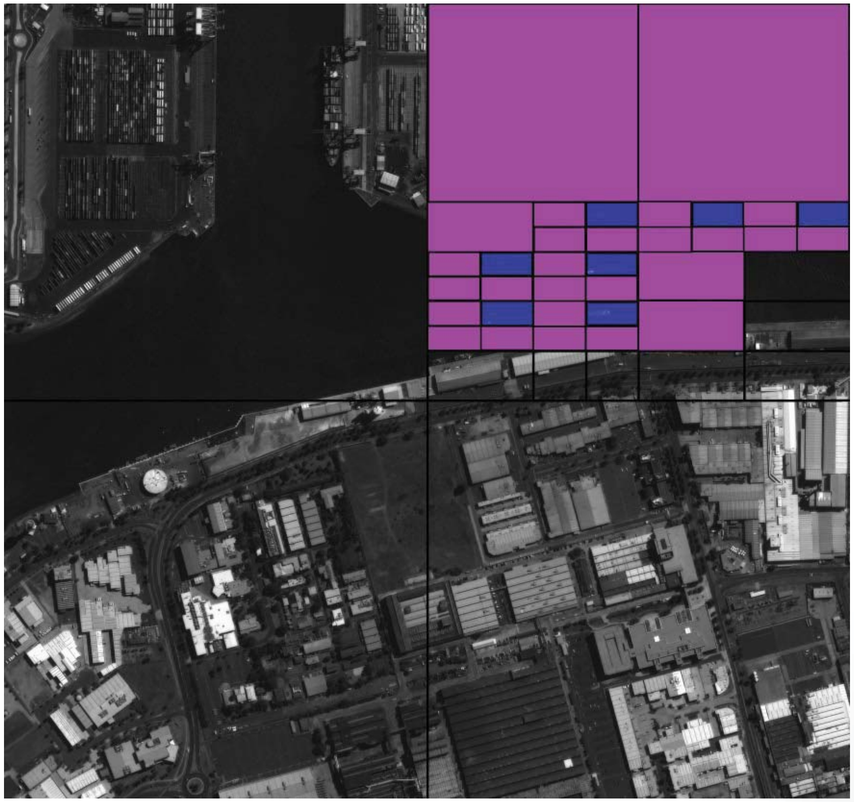
Our improvement to the parallel sampler

Problem



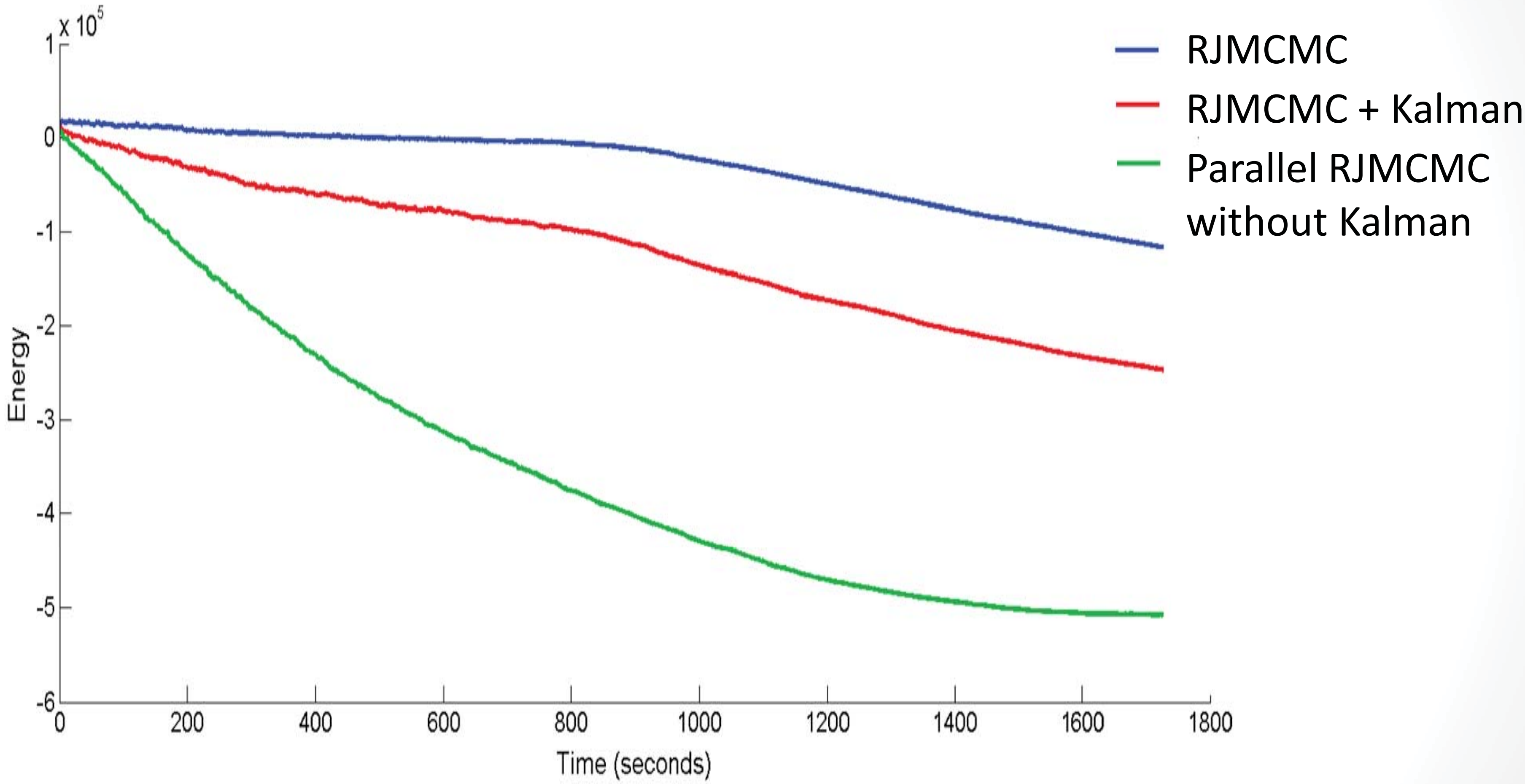
Large boat is split between two neighboring cells

Solution



Take the configurations in the neighboring cells into consideration

Did time efficiency increase?



Parallel implementation significantly reduces computation times!

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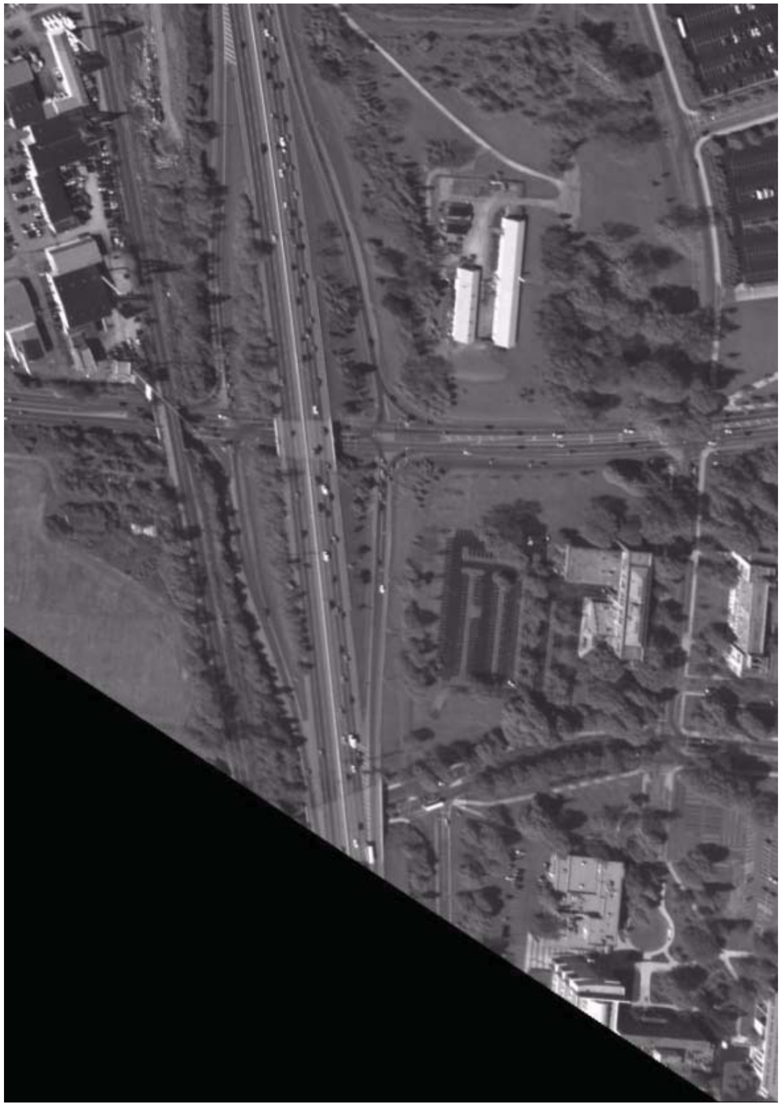
Data sets

- 2 different data sets:
  - UAV (unmanned aerial vehicle) data (Public available data set)
  - Satellite data (Airbus Defense and Space)
    - Low temporal frequency (~1-2Hz)
    - High temporal frequency (30Hz)

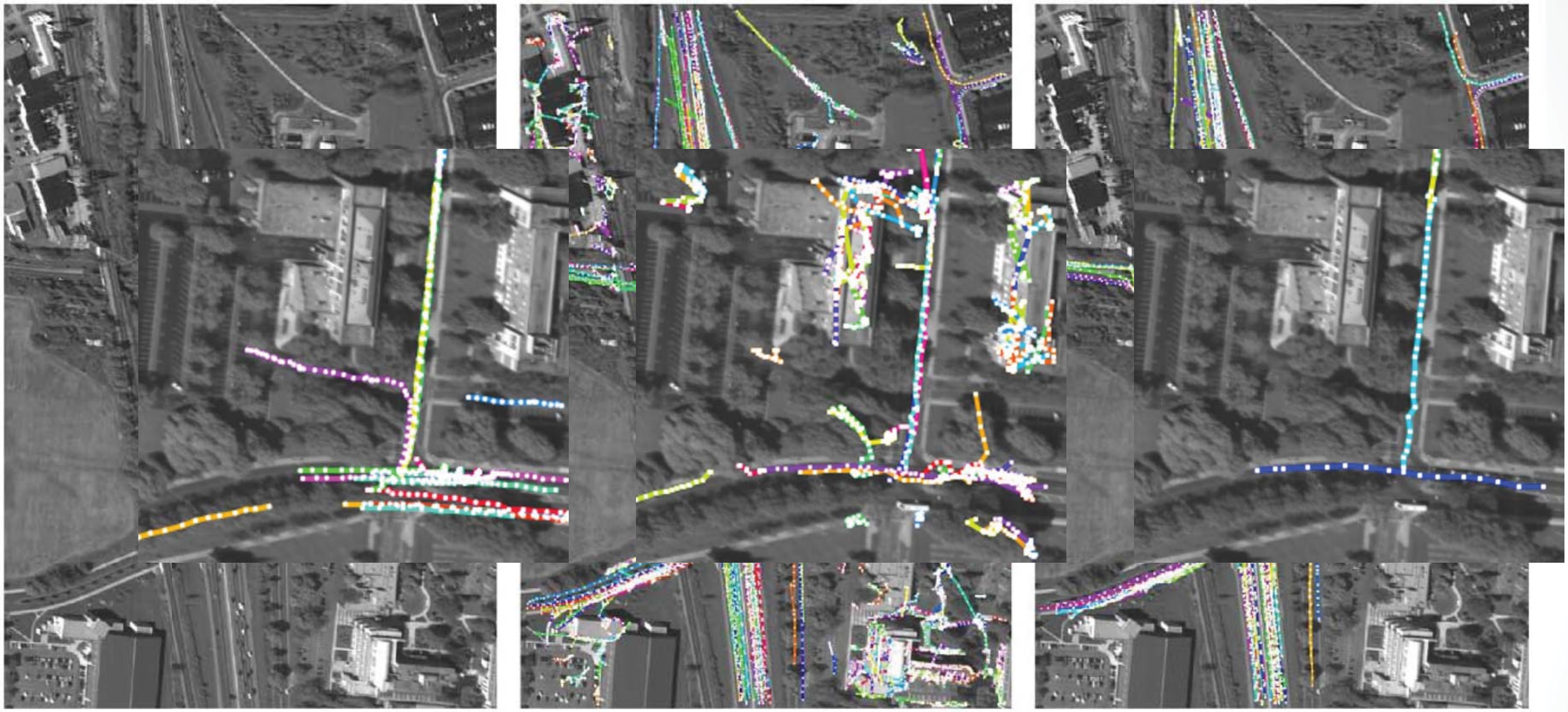
UAV data – low temporal frequency



COLUMBUS LARGE IMAGE FORMAT
(CLIF) 2006 data set

Provided by:
The Sensor Data Management System,
U.S. AirForce
https://www.sdms.afrl.af.mil

UAV data – low temporal frequency



Original image [Prokaj2011] Proposed

Method	Tracks				Detections			
	Number	Paired	Missed	Spurious	Number	Paired	Missed	Spurious
GT	322				12304			
[Prokaj2011]	674	207	115	467	17823	**5139**	**7165**	12684
MHT	3456	**254**	**68**	3202	85380	1189	11115	60069
Prop.	238	179	143	**59**	6466	4480	7824	**1986**

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Satellite data – low temporal frequency

Tracking results © INRIA / AYIN

Average computation time: 12 sec / frame on a cluster with 512 cores
Image size: 1600 x 900 pixels

Satellite data – high temporal frequency

Tracking results

Average computation time: 8 sec / frame on a cluster with 512 cores
Image size: 1600 x 900 pixels

Satellite data – high temporal frequency

Tracking results © INRIA / AYIN

Average computation time: 10-11 sec / frame on a cluster with 512 cores
Image size: 1600 x 900 pixels

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Conclusions

- Two novel spatio-temporal marked point process models for the detection and tracking of moving objects
- Automatic or semi-automatic parameter estimation using linear programming
- Integrated RJMCMC sampler with Kalman-like moves
- Efficient parallel implementation of the RJMCMC sampler
- Good results on different types of data

Critical analysis

Advantages

- Detection of weakly contrasted objects
- Consistent trajectories
- Object interactions modeling
- Robustness to noise and data quality
- Good results on different data sets

Drawbacks

- Real-time processing only in exceptional cases
- Simple shape modeling

Perspectives

- Design a hierarchical model that integrates both low-level constraints between individual objects and high-level constraints between trajectories
- Multi-marked process to distinguish between various object classes
- Model traffic density instead of individual trajectories
- Optimization process should be further improved to make such models competitive

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