Marked Point Processes For Object Detection and Tracking in High Resolution Images: Applications to Remote Sensing and Biology

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Optical airborne and space-borne systems

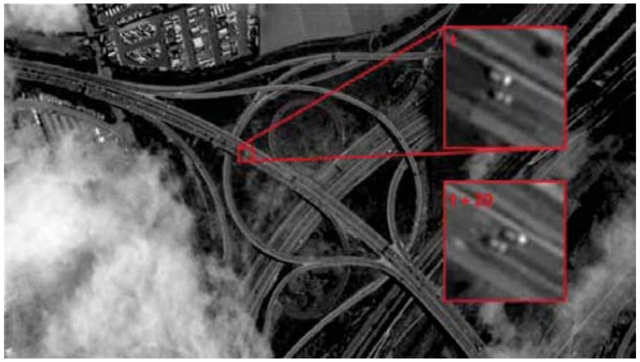
- UAVs (unmanned aerial vehicles)
  - Sub-meter ground sampling resolution imagery
  - Unstable platform

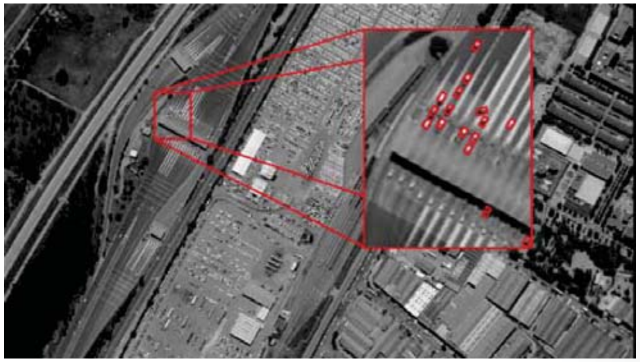
- Low-orbit satellites
  - Sub-meter ground sampling resolution imagery
  - Stable platform
  - High-definition video of up to 90 seconds at 30 frames / second

- Geostationary satellites
  - 1km (or lower) ground sampling resolution imagery
  - Low temporal frequency (1 frame every few minutes)

Challenges

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

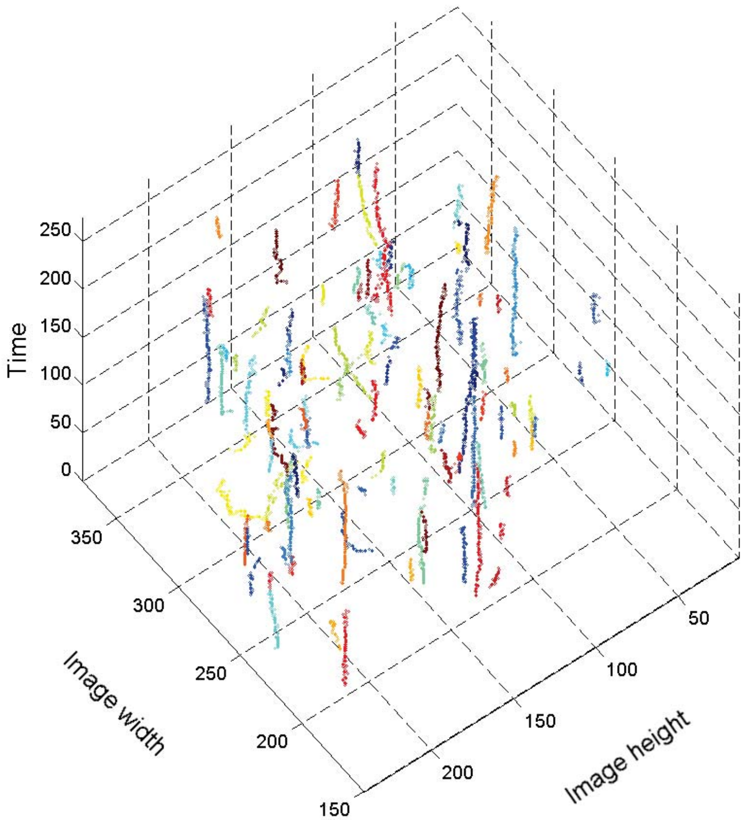




Multiple Object Tracking (MOT)

- **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**

Patterns and stochastic geometry

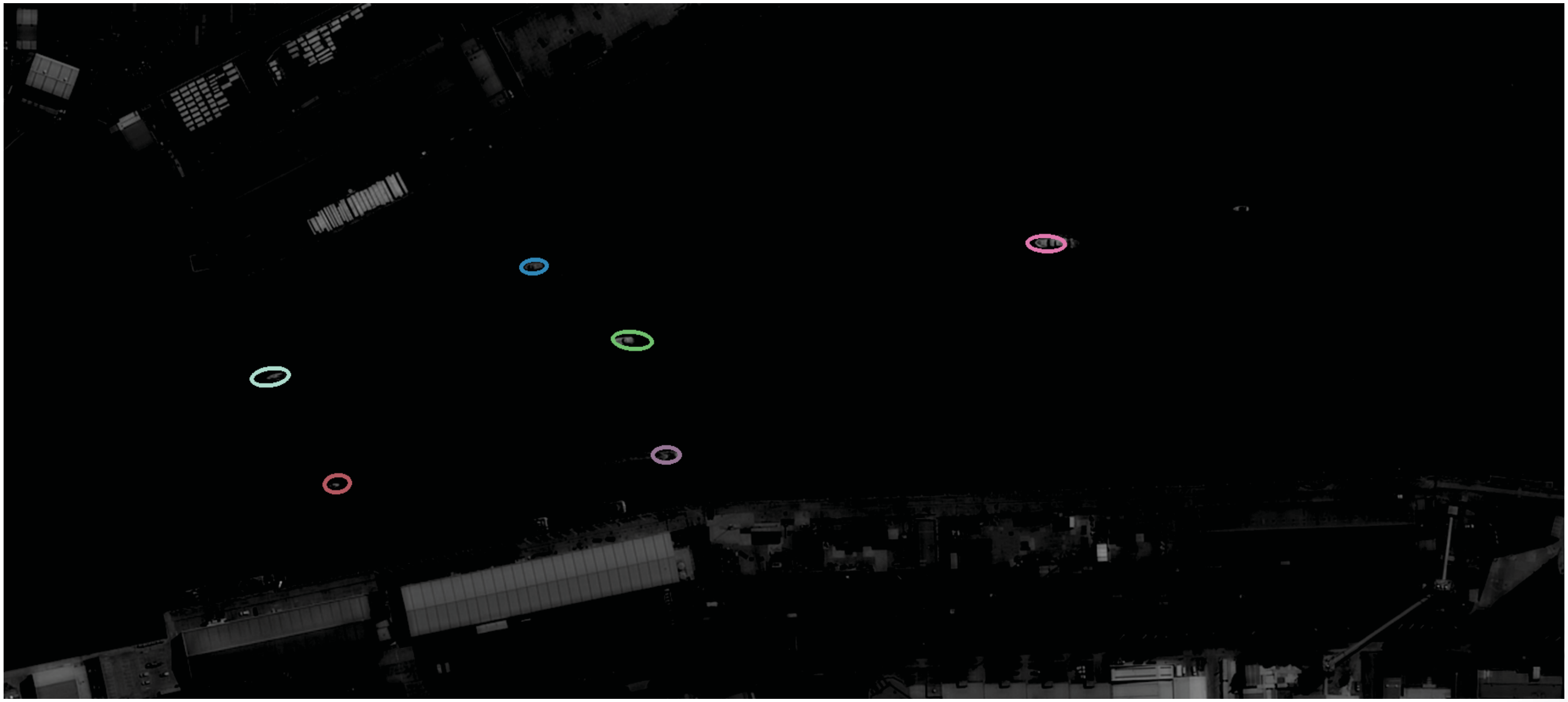


- Object tracking as a spatio-temporal marked point process
- How to model and simulate such a spatio-temporal point process?

Overview

- Models
  - Model formulation
  - Quality model vs. Statistical model
- Parameter learning
  - Linear programming
  - Parameter learning as a linear program
- Simulation
  - Standard RJMCMC
  - Parallel implementation of RJMCMC
- Results
- Conclusions and perspectives

Brief Insights



Sample output on satellite data © Airbus D&S

Marked point process of ellipses

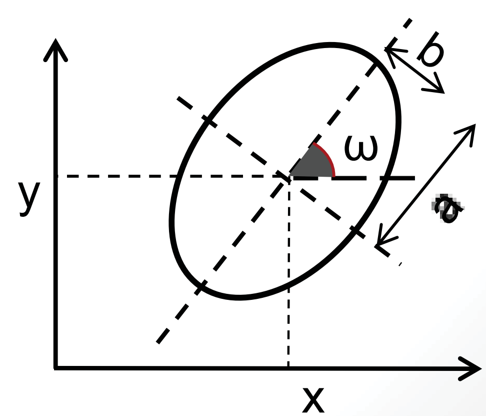
- Center of the ellipse is a point in the point process
- Marks:
  - Geometric marks: semi-major axis, semi-minor axis, orientation
  - Additional mark: label

$$W = K \times M$$

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

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

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



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:

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

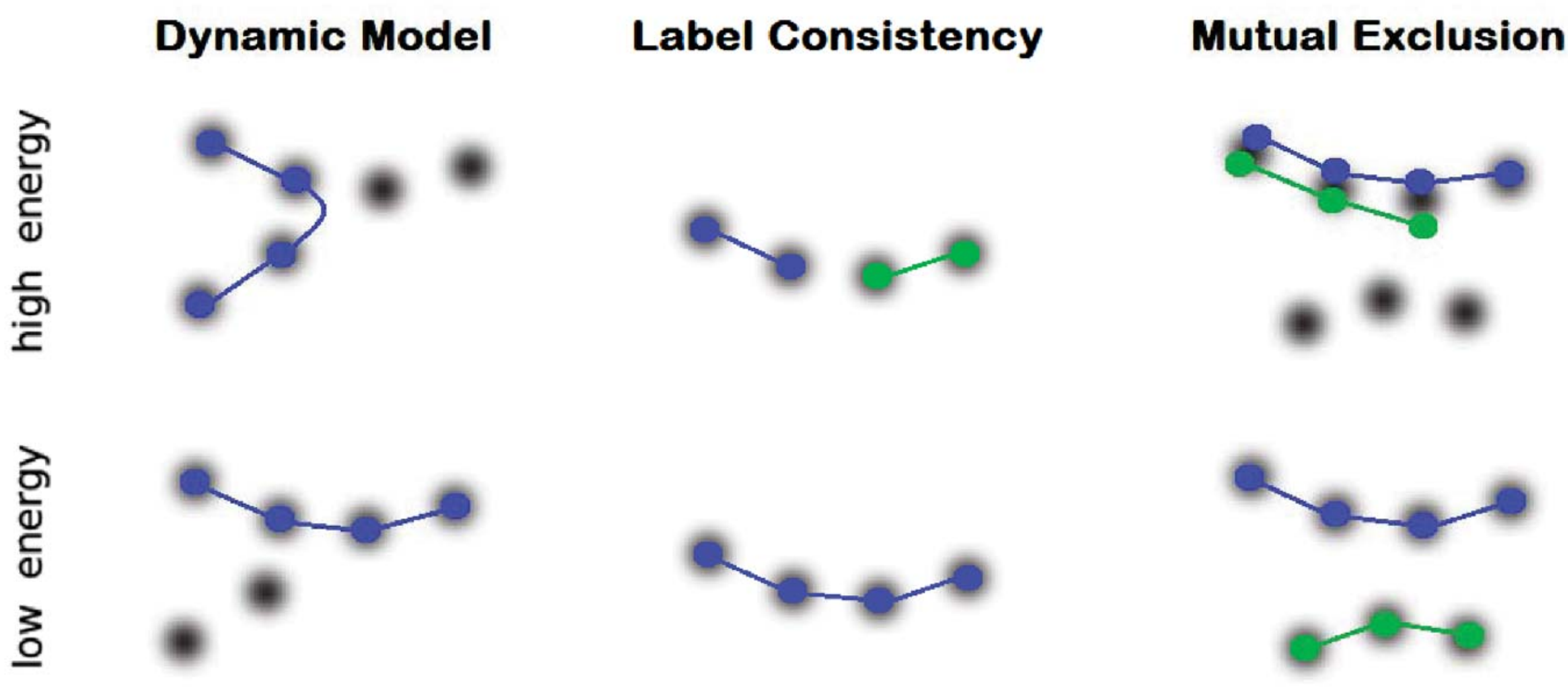
  - The most likely configuration is given by:

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

  - The process energy is composed of two energy terms:

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

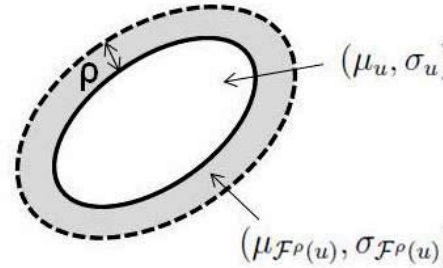
Internal energy



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:
  - $\boldsymbol{H_0}$: The window covers only the background without any target being present
  - $\boldsymbol{H_1}$: 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

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

Internal energy

Statistical model

External energy

$$
\begin{aligned}
U_\theta(\mathbf{X},\mathbf{Y}) \quad = \quad & \boxed{\gamma_{stat}U_{stat}^{ext}(\mathbf{X}|\mathbf{Y})} + \\
& \boxed{\gamma_{dyn}U_{dyn}^{int}(\mathbf{X}) + \gamma_{label}U_{label}^{int}(\mathbf{X}) + \gamma_{o}U_{overlap}^{int}(\mathbf{X})}
\end{aligned}
$$

Internal energy

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Linear programming

- A linear program has the following form

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

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

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

- Given two configurations **X** and **X'**
- Only the ratio of their posterior distributions $\pi(\mathbf{X}')/\pi(\mathbf{X})$ needs to be computed
- We can create inequalities of the form

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

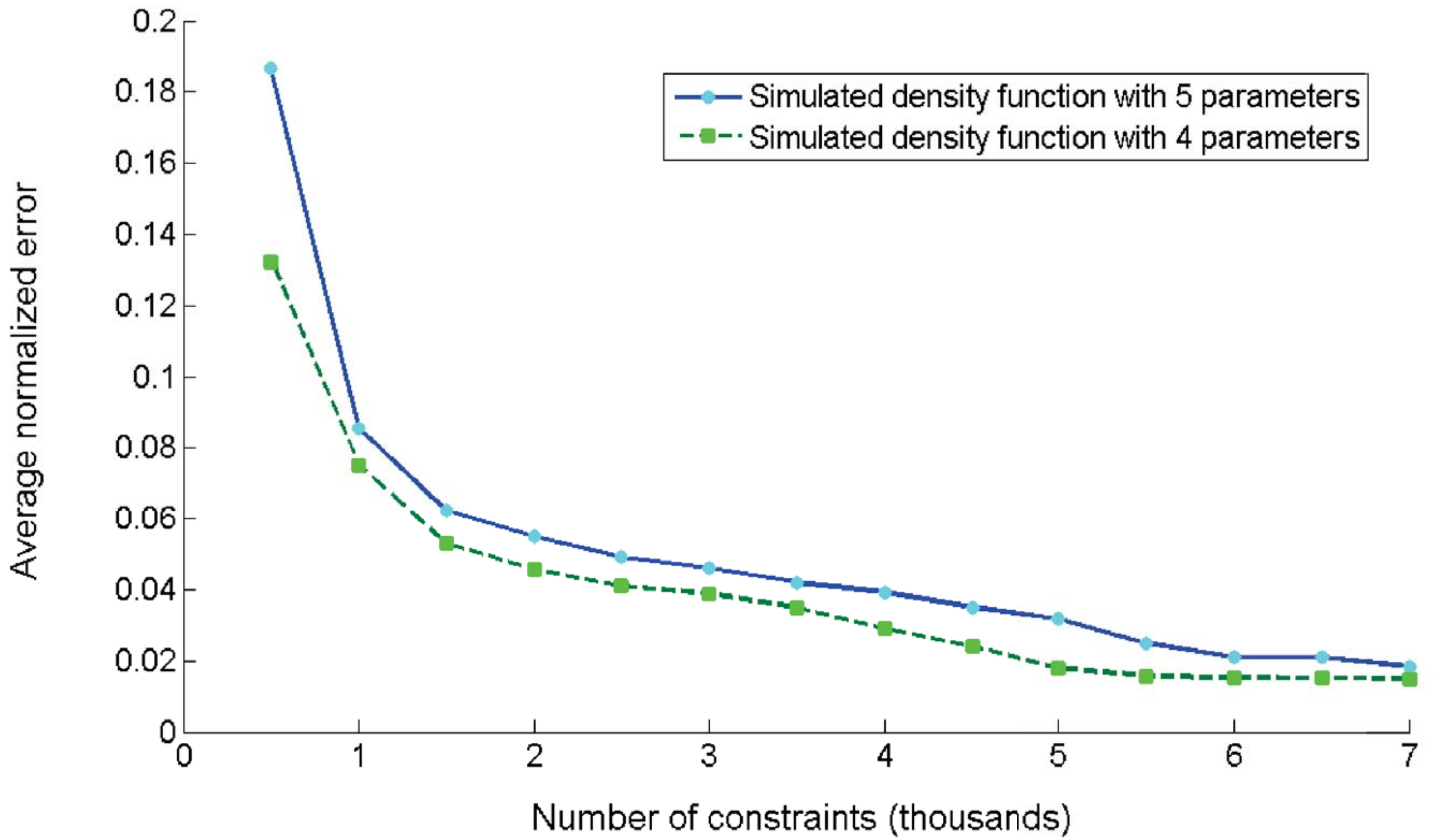
- If we have ground truth information **X*** then

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

- 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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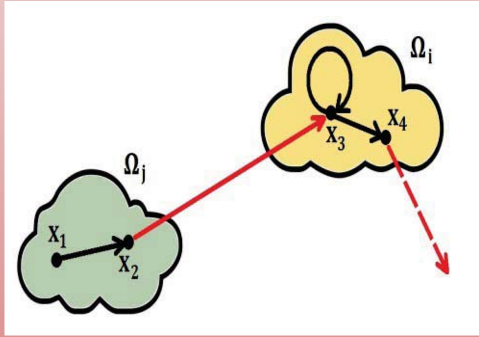
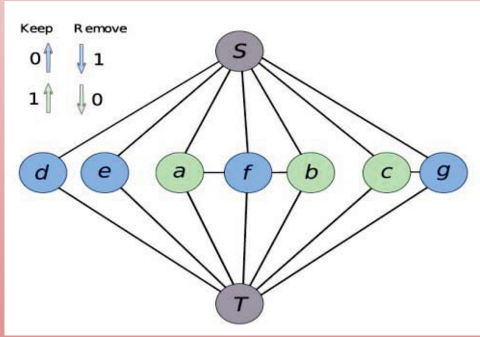
Related samplers

RJMCMC



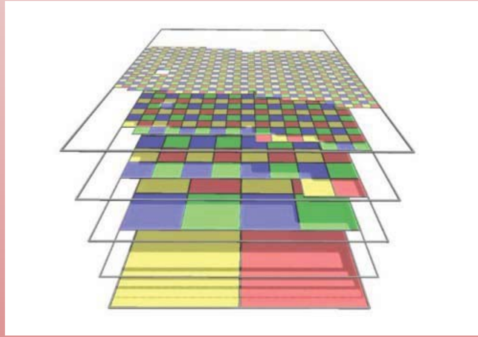
[Green1995]

MBD and MBC



[Descombes2009]
[Gamal2011]

P-RJMCMC



[Verdie2012]

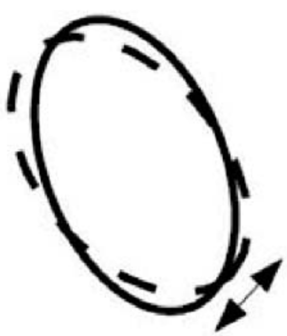
Classic RJMCMC

- 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

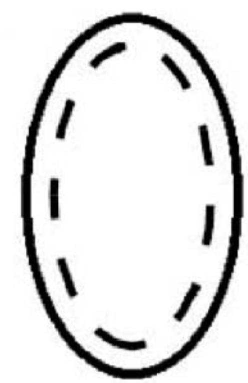
- Birth and Death
  - Birth:
    - Add a new object to the configuration
  - Death:
    - Remove one object from the configuration
- Local transformations

Rotation



Translation

Scale



State dependent mixing

1. With probability $Q_m(\mathbf{X}, \Omega)$ choose a kernel Q_m or with probability $1 - \sum_m Q_m(\mathbf{X}, \Omega)$ let the state unchanged $X_{i+1} = \mathbf{X}$;

2. Simulate $\mathbf{X}'$ according to the normalized kernel chosen:

$$\mathbf{X}' \sim \frac{Q_m(\mathbf{X}, \cdot)}{Q_m(\mathbf{X}, \Omega)}$$

3. Compute the Green ratio:

$$R_m(\mathbf{X}, \mathbf{X}') = \frac{f_m(\mathbf{X}', \mathbf{X})}{f_m(\mathbf{X}, \mathbf{X}')}$$

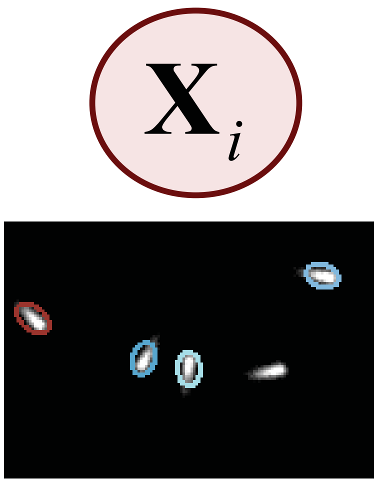
4. Accept the perturbation with probability $\alpha_m(\mathbf{X}, \mathbf{X}') = \min(1, R_m(\mathbf{X}, \mathbf{X}'))$or reject otherwise.

Optimization

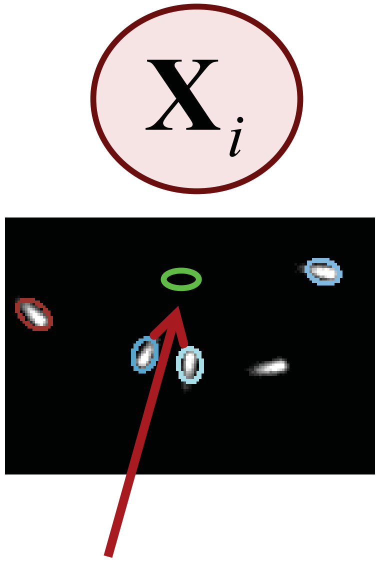
- Reversible Jump – MCMC embedded in a Simulated Annealing scheme

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

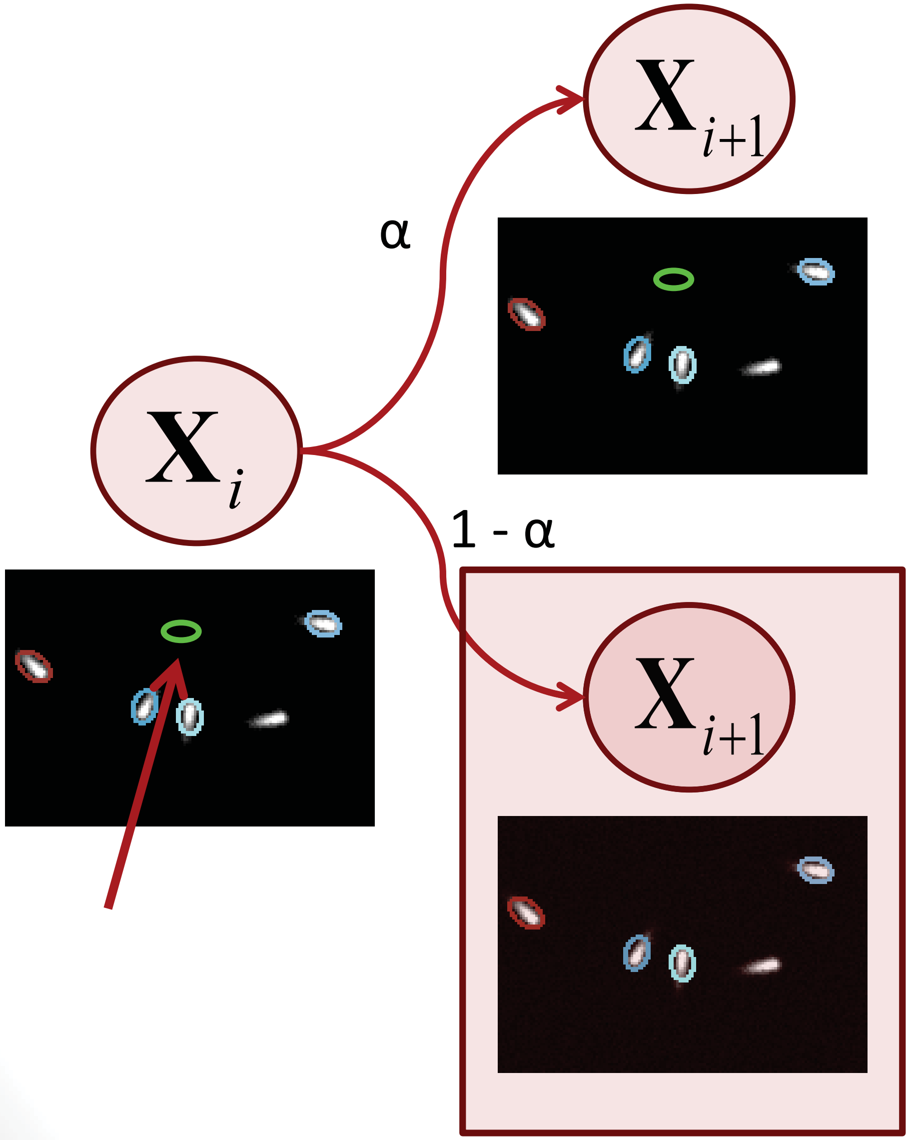
RJMCMC sampler



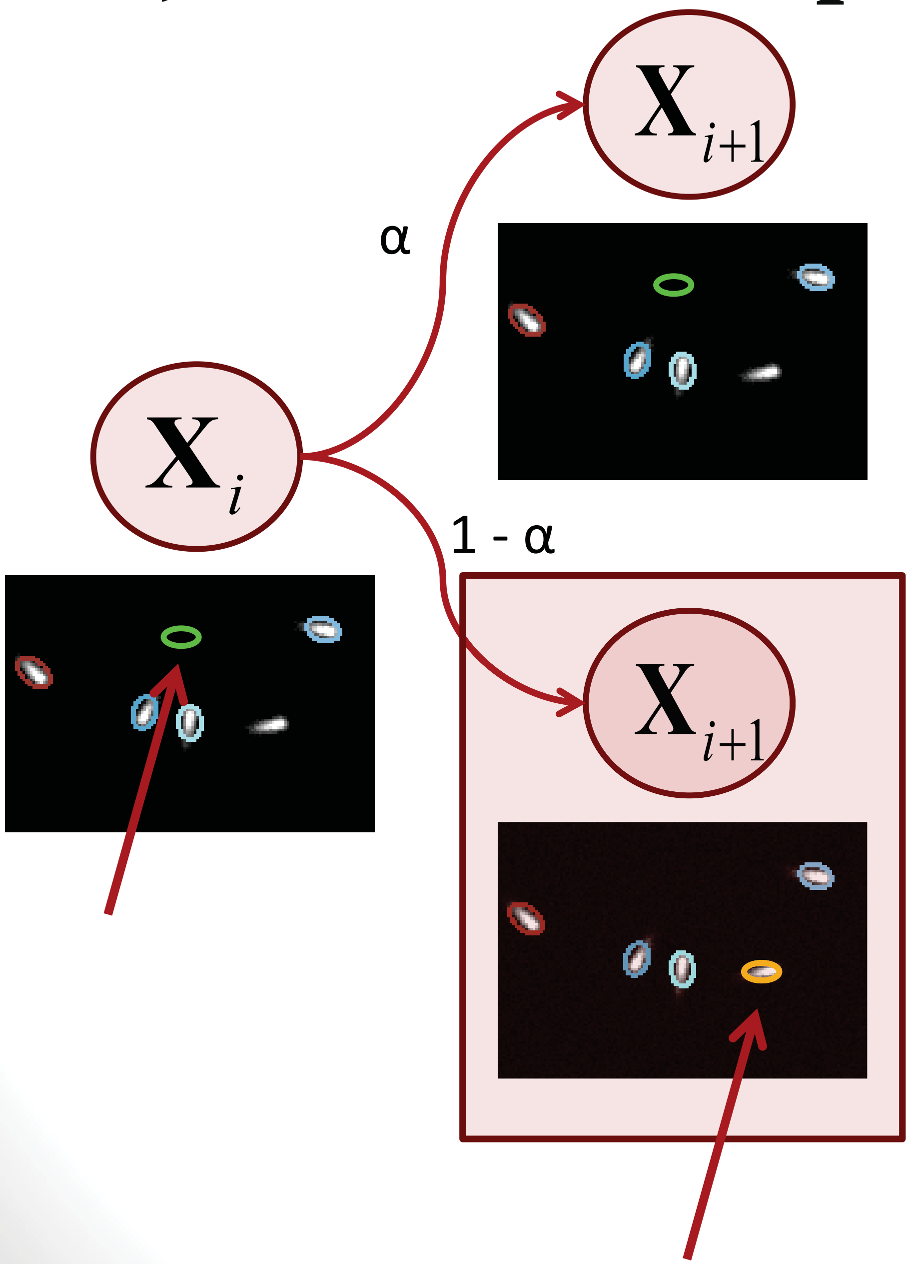
RJMCMC sampler



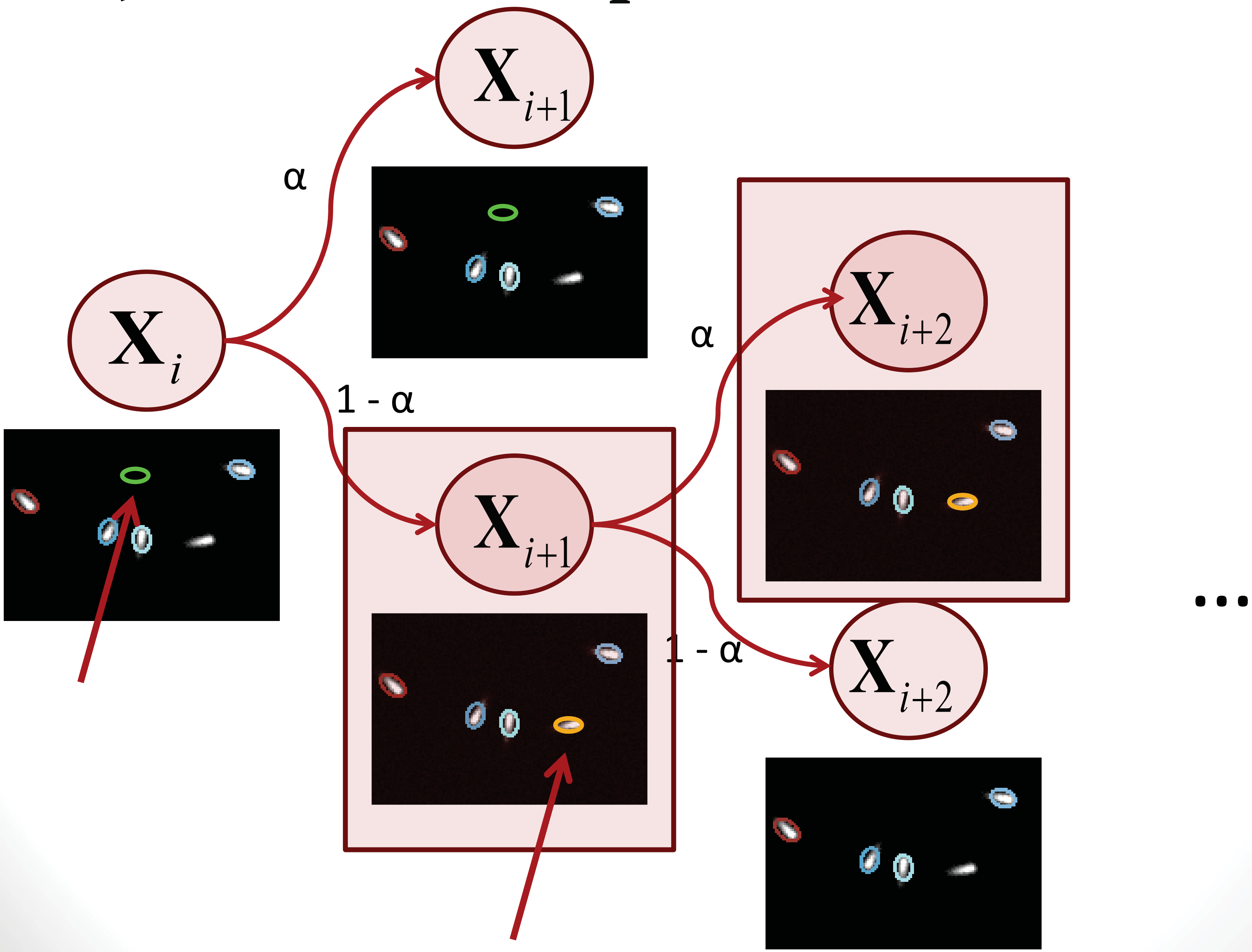
RJMCMC sampler



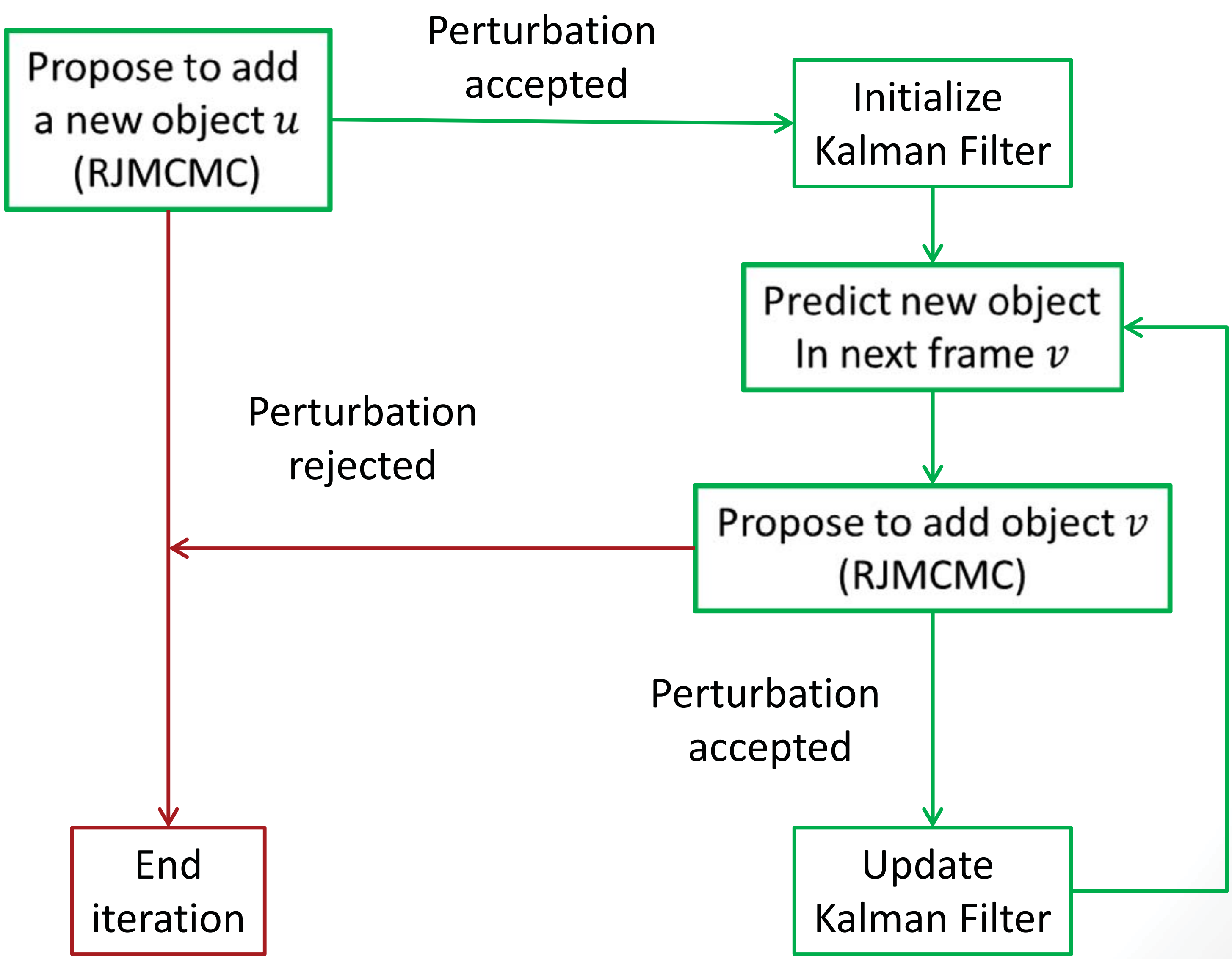
RJMCMC sampler



RJMCMC sampler

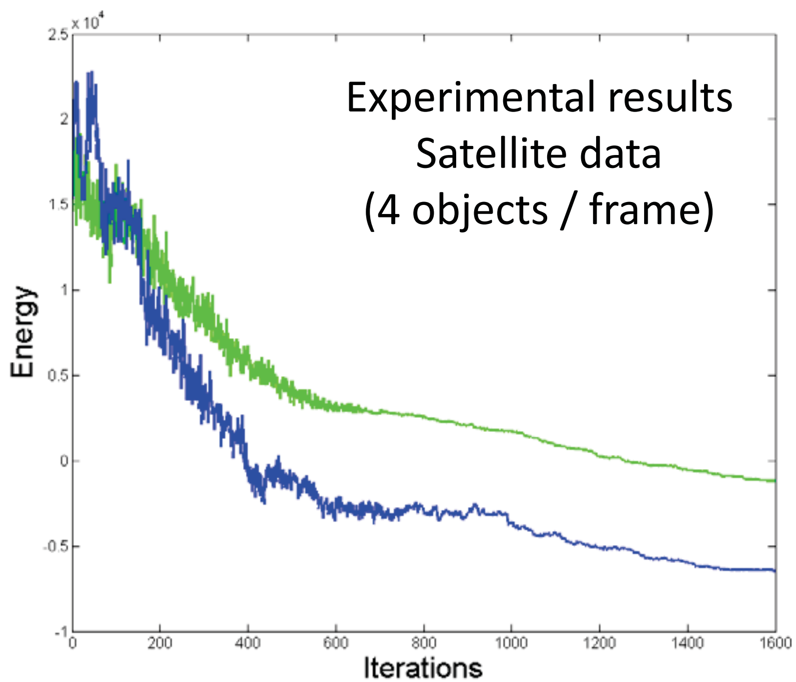


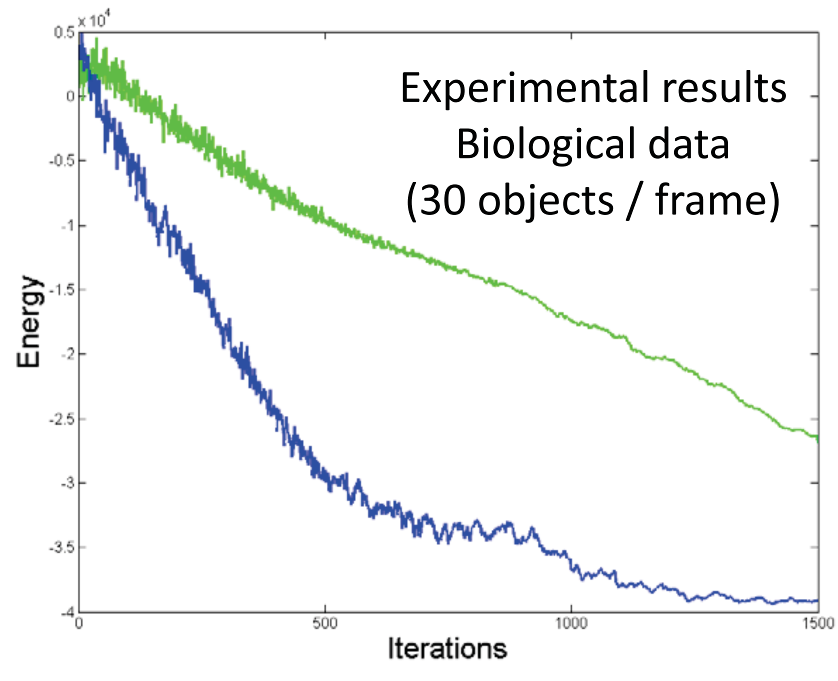
Adding Kalman-inspired births



Did time efficiency increase?

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





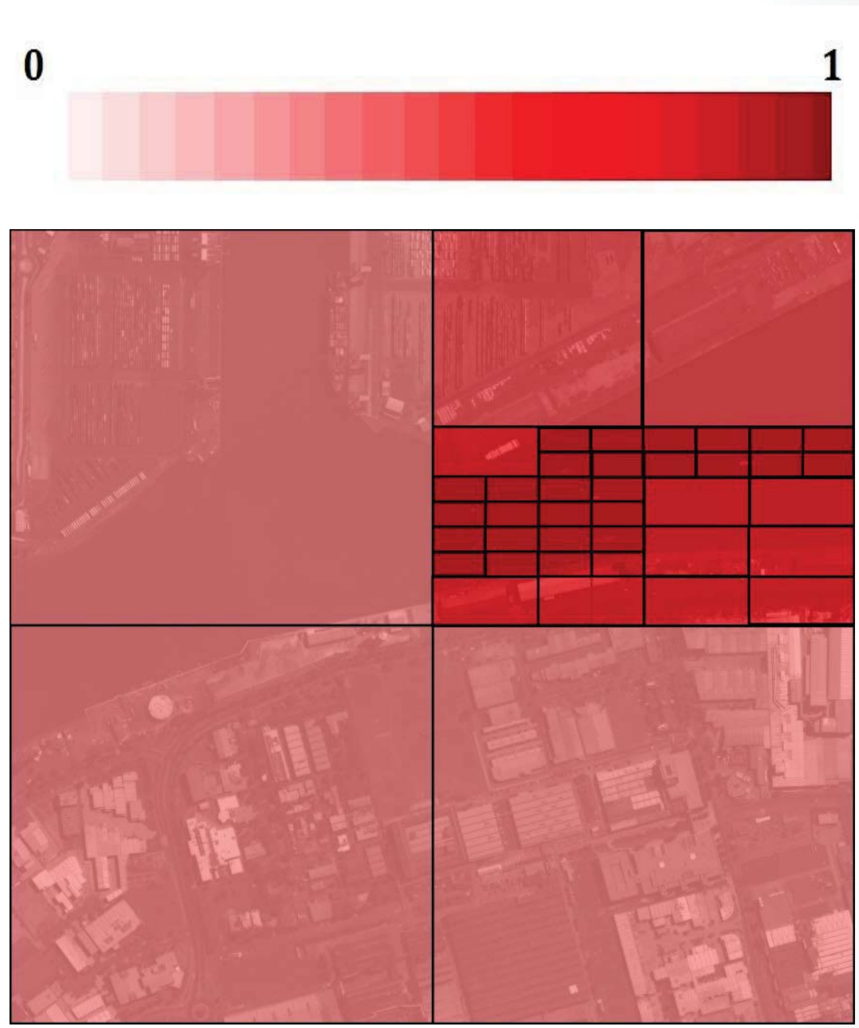
Kalman-inspired births reduce computation times!

Parallel implementation of RJMCMC [Verdie2012]

- Data-driven space partitioning
- Locally conditional independent perturbations

Image with boats © Airbus D&S

Parallel implementation of RJMCMC

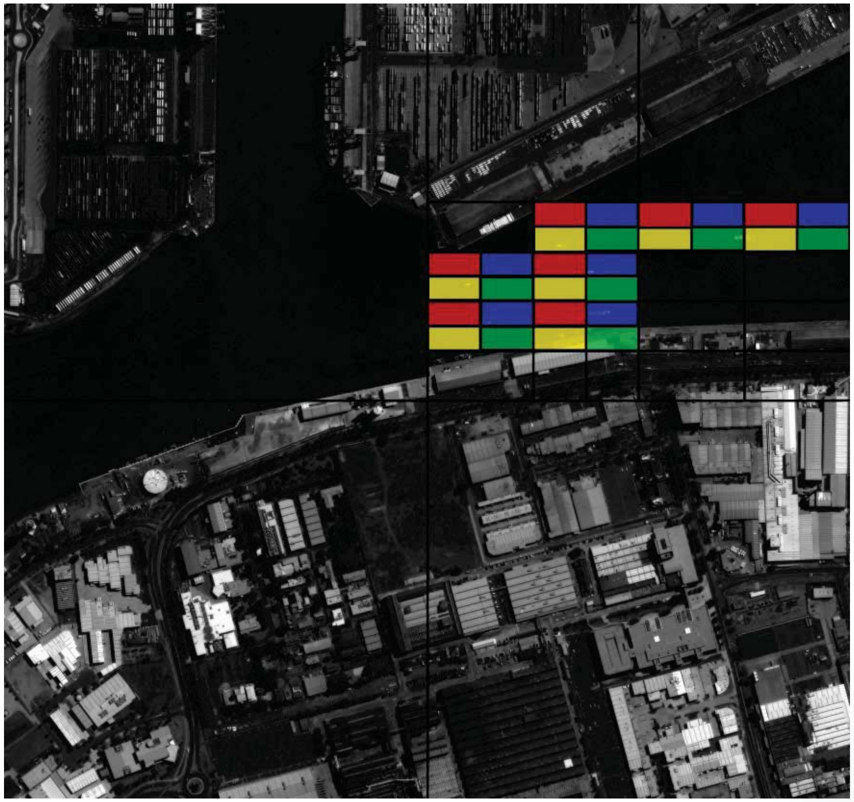


- Data-driven space partitioning
- Locally conditional independent perturbations

Probability that objects exist in each part of the image

Parallel implementation of RJMCMC

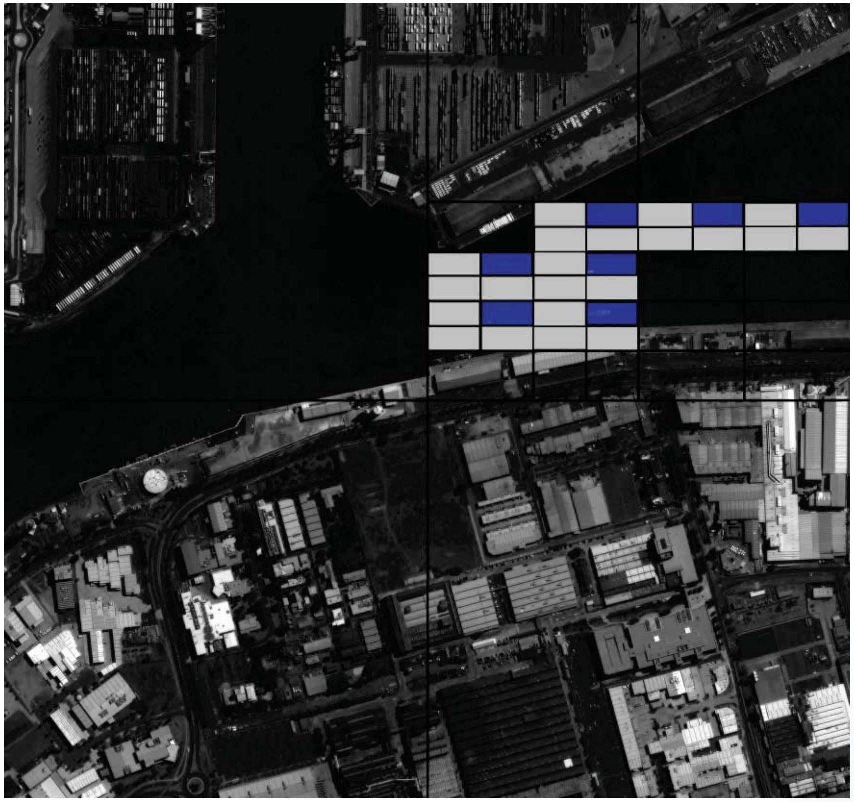
- Data-driven space partitioning
- Locally conditional independent perturbations



Color coding of quad-tree leafs

Parallel perturbations [Verdie2012]

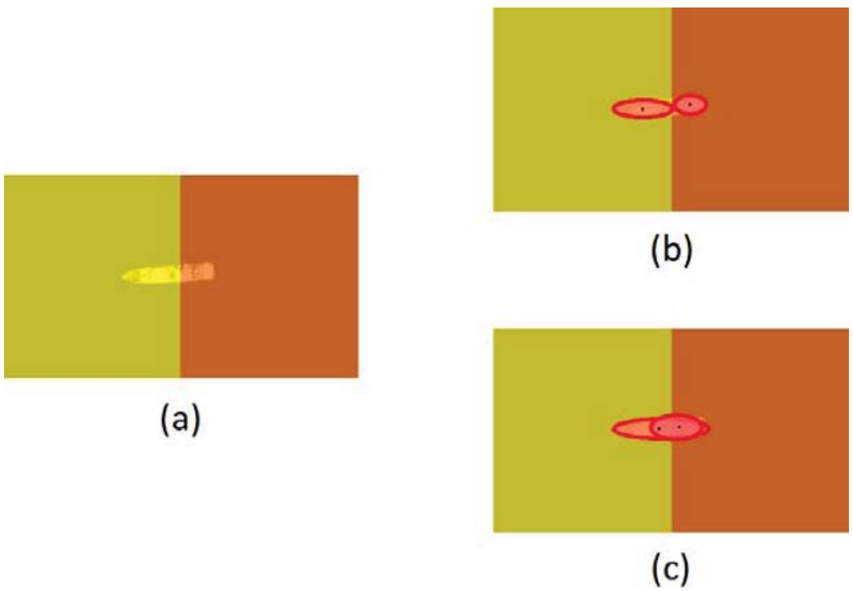
- A color is randomly chosen
- Perturbations are performed in all cells of the chosen color in parallel



Color blue is randomly chosen

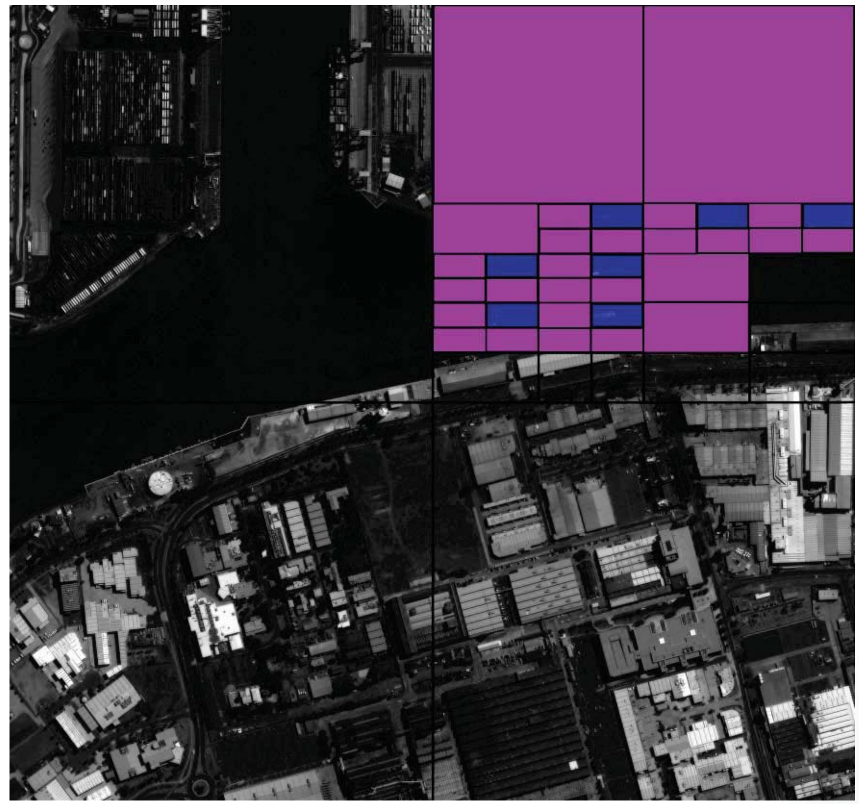
Our improvement to the parallel sampler

Problem



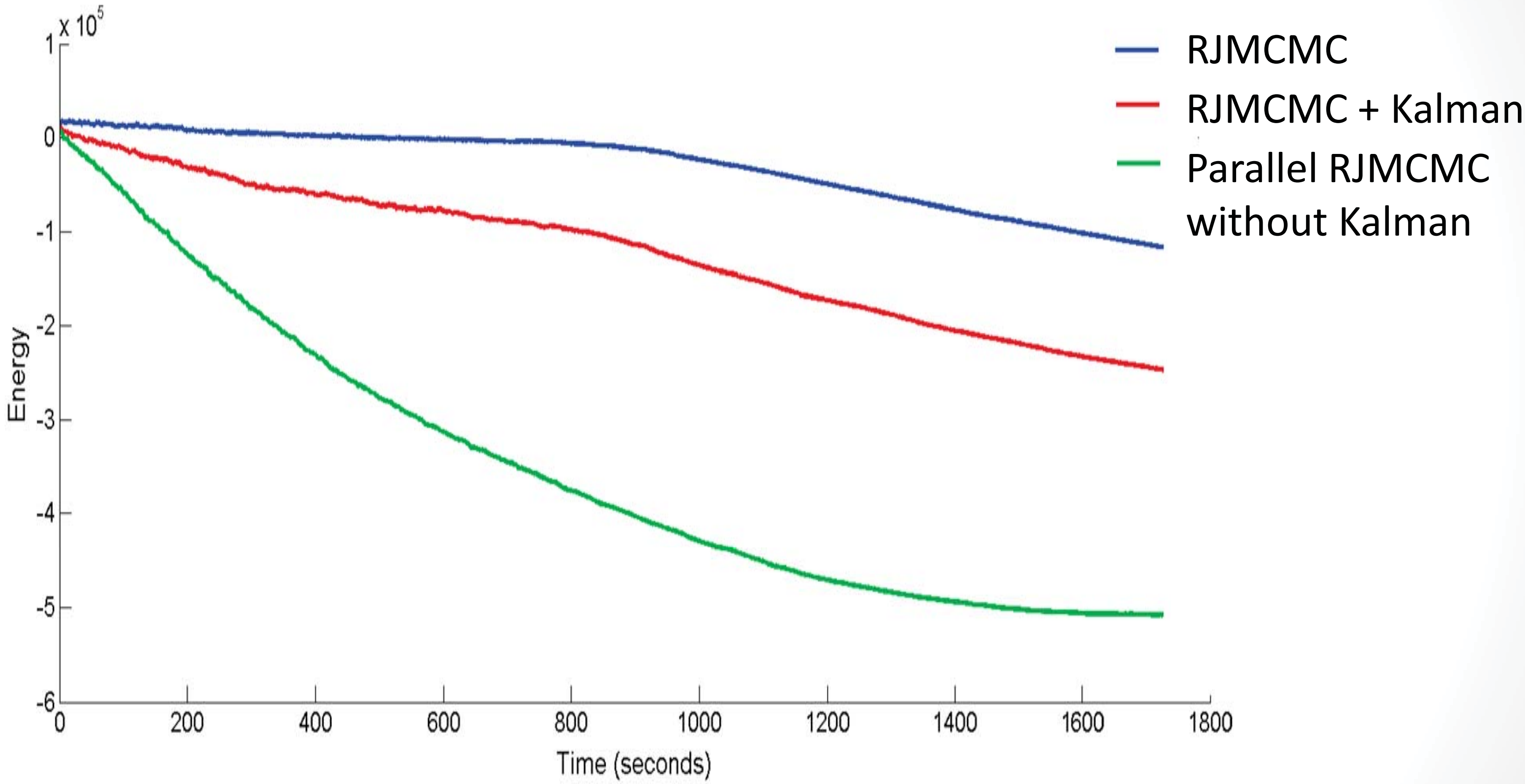
Large boat is split between two neighboring cells

Solution



Take the configurations in the neighboring cells into consideration

Did time efficiency increase?



Parallel implementation significantly reduces computation times!

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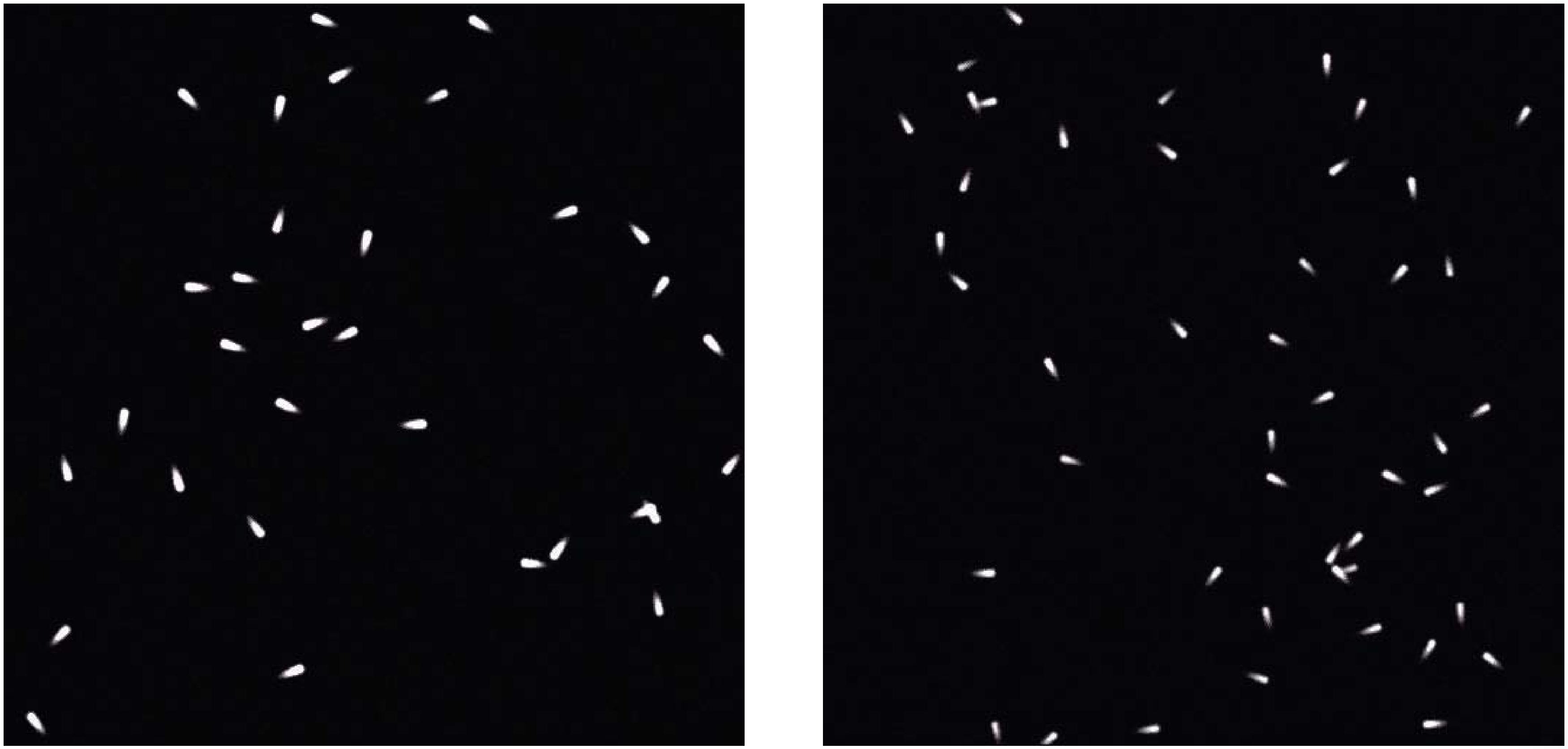
Data sets

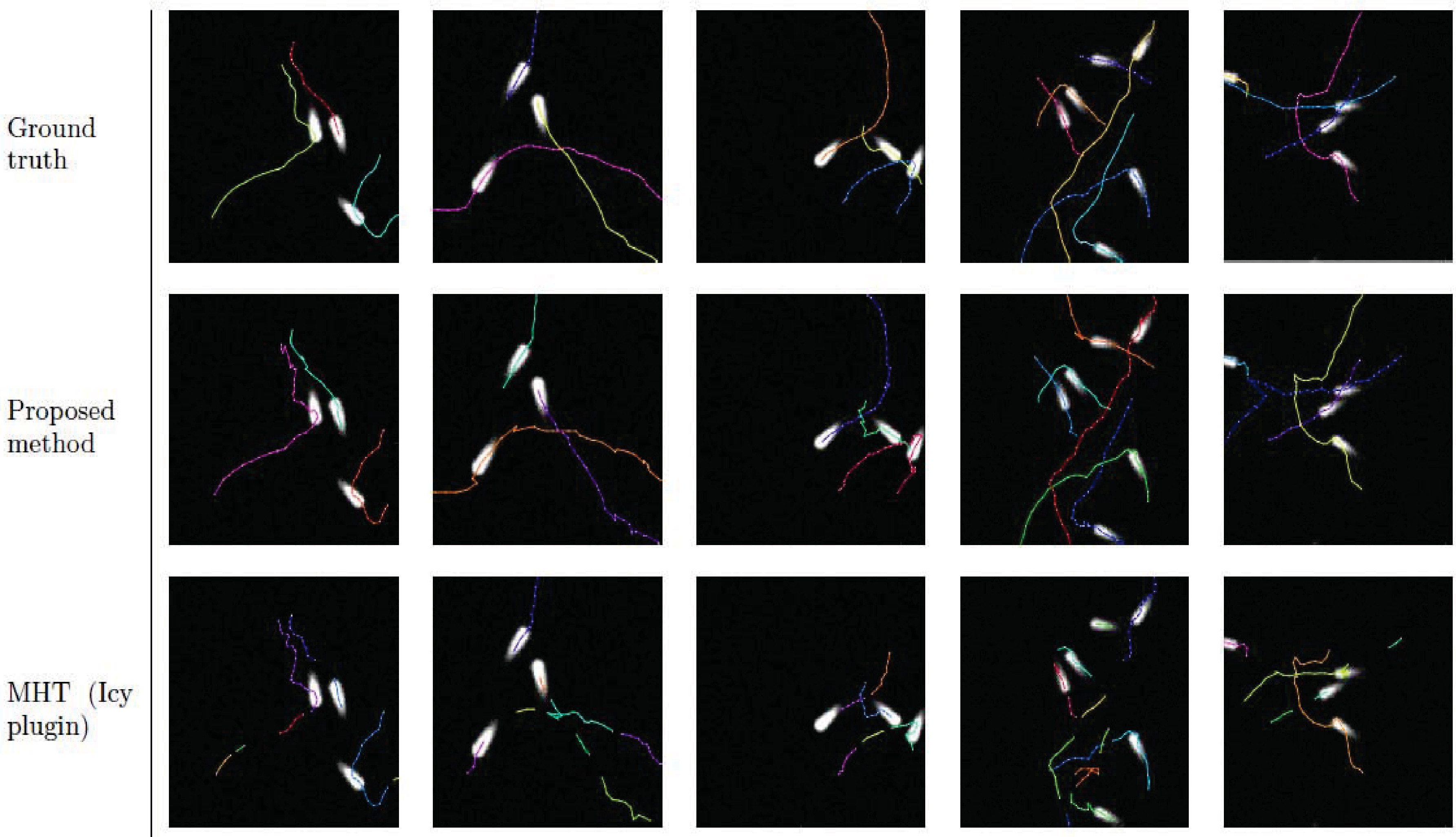
- 4 different data sets:
  - Synthetic biological benchmarks (Pasteur Institute)
    - 100 frames / sequence
    - Different levels of noise
  - Real biological sequence (Curie Institute, fluorescence image sequence)
    - 300 frames / sequences
  - UAV (unmanned aerial vehicle) data (Public available data set)
  - Satellite data (Airbus Defense and Space)
    - Low temporal frequency (~1-2Hz)
    - High temporal frequency (30Hz)

Synthetic biological benchmarks



*Generated using the publicly available software ICY courtesy of the Quantitative Analysis Unit at the Pasteur Institute and J.-C. Olivo-Marin (http://icy.bioimageanalysis.org)

Synthetic biological benchmarks

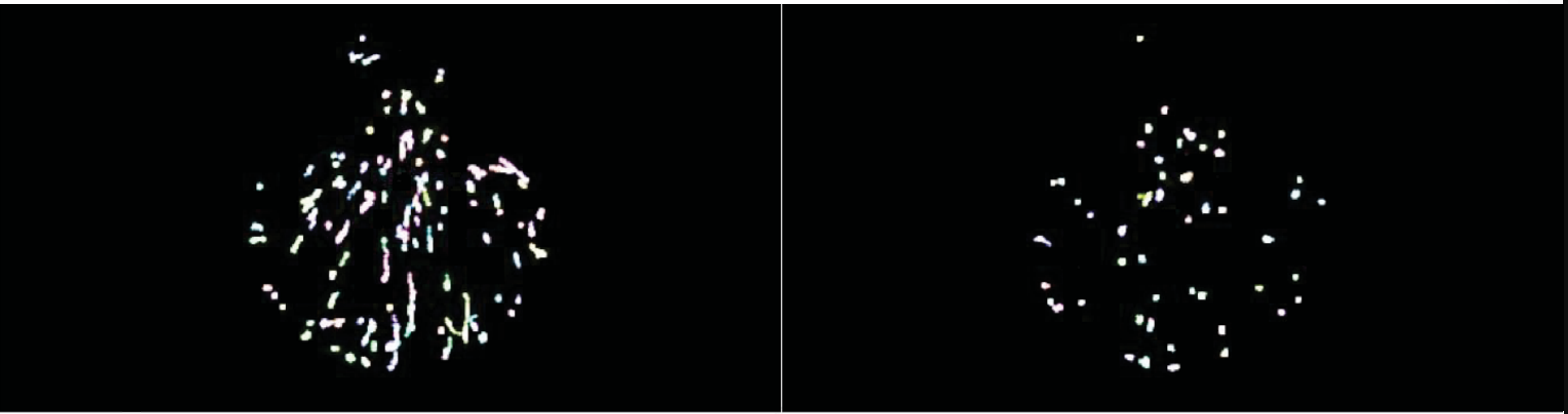


Comparison between the results obtained using the built-in MHT tracker within Icy and the proposed method for the three synthetic image sequences.

*Generated using the publicly available software ICY courtesy of the Quantitative Analysis Unit at the Pasteur Institute and J.-C. Olivo-Marin (http://icy.bioimageanalysis.org)

Real biological data

- Total internal reflection fluorescence image sequence (TIRF)*



Detection and tracking results on a real TIRF image sequence.

Data set	No. reference tracks (MHT)	No. candidate tracks (Proposed algorithm)	Similarity between tracks	Similarity between detections
TIRF Seq.	512	346	0.4042	0.2445

Comparison between the results obtained using the built-in MHT tracker within Icy [6] and the proposed method for one real TIRF image sequence. Note however, that the output of the MHT tracker should not be taken as ground truth information.

* (by courtesy of J. Salamero, PICT IBiSA, UMR 144 CNRS Insitut Curie)

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**

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

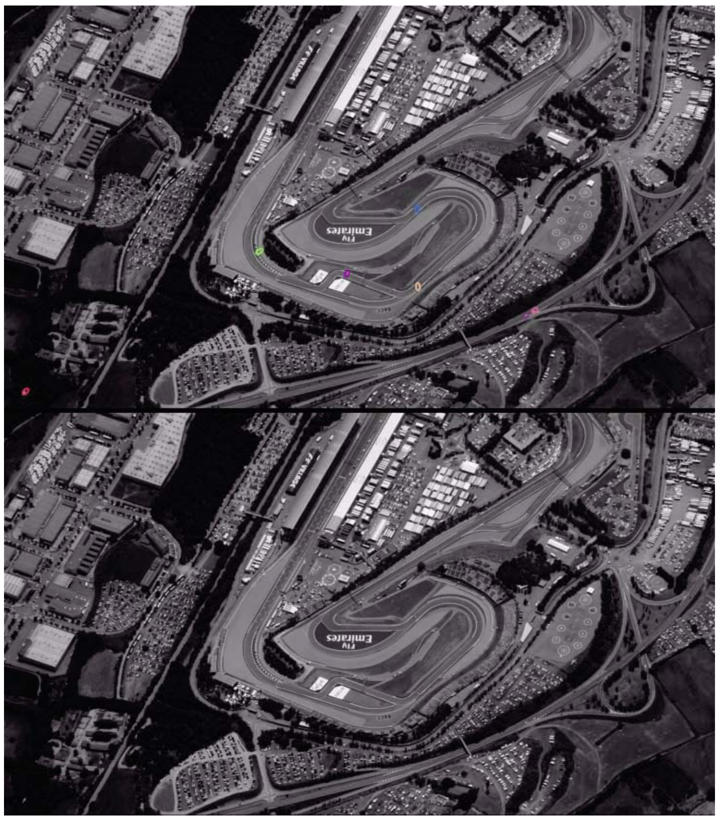
Satellite data – high temporal frequency

Tracking results

© INRIA / AYIN

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

Satellite data – high temporal frequency



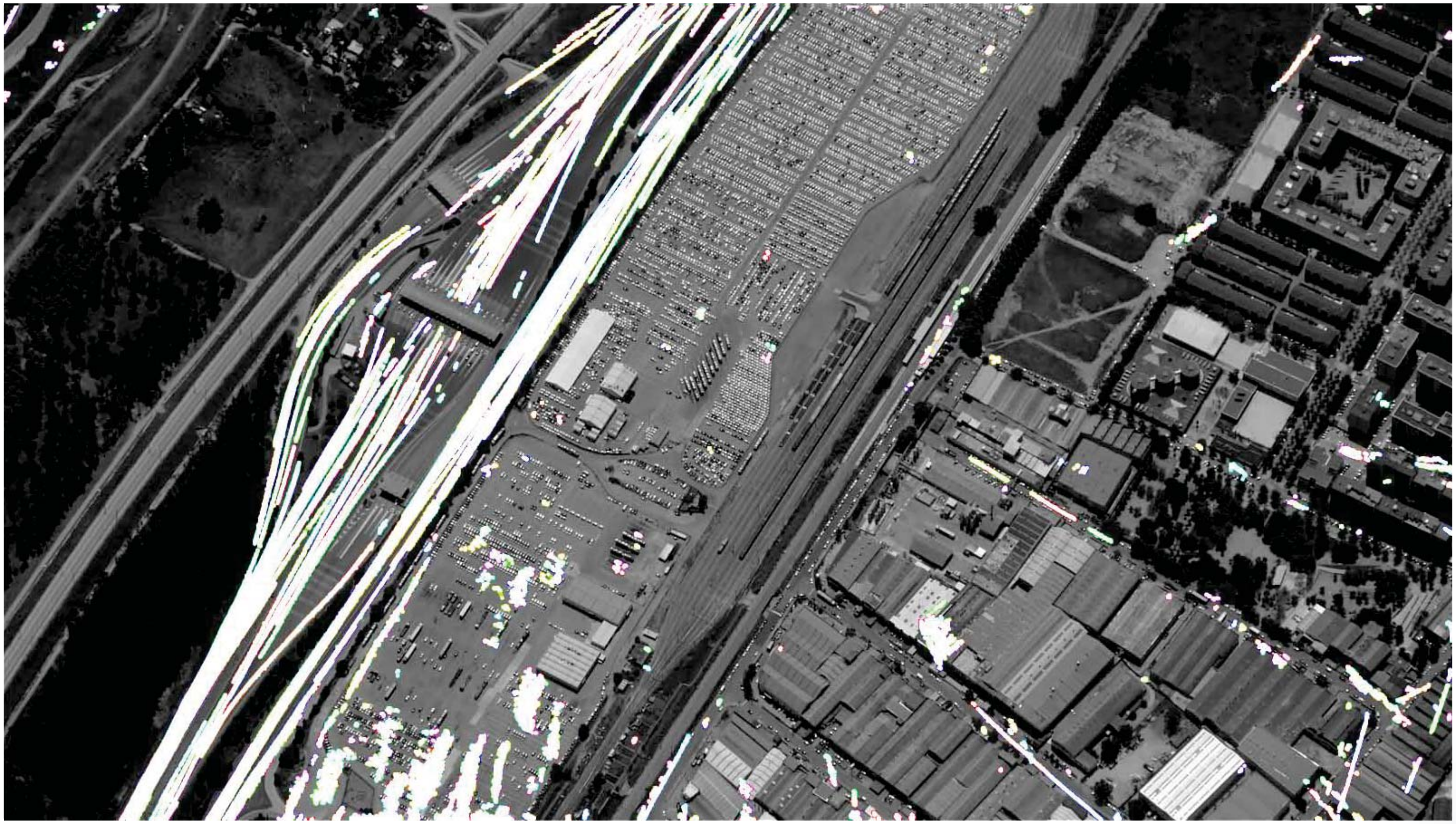
Tracking results

© INRIA / AYIN

Average computation time: 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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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

Conclusions

- Novel spatio-temporal marked point process model for the detection and tracking of moving objects
- Automatic or semi-automatic parameter estimation using linear programming
- Efficient parallel implementation of the RJMCMC sampler
- Good results on different types of data

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Thank you!

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Backup

- Tracking by detection / Track before detect
- Data association based methods
- Random Finite Sets based methods

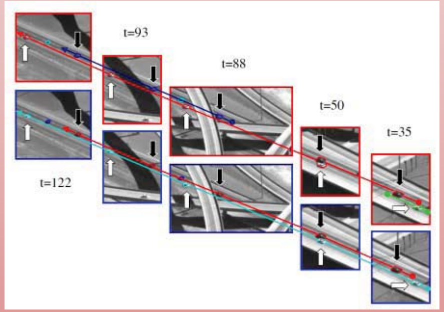
Tracking by detection

- Use a detector to pre-detect targets
- Use a tracker to solve the data association problem

- Common algorithms
  - Multiple Hypothesis Tracking (MHT) [Bar-Shalom2007, Saleemi2013]
  - Joint Probabilistic Data Association Filter (JPDAF) [Kang2005, Wu2009]
  - MCMC Data Association – partition discrete set of detections into tracks [Yu2009]

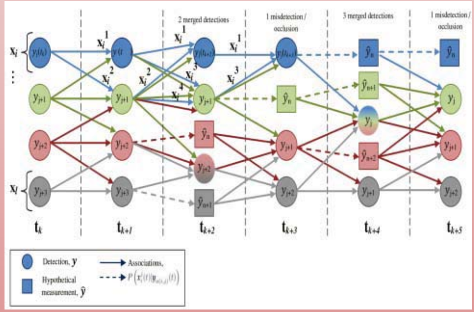
Data-association based methods

NN-app



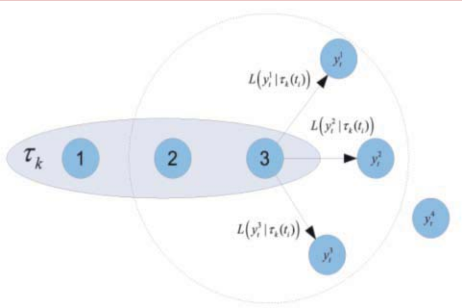
[Perera2006]

DD-MCMCDA



[Yu2008]

MHT



[Saleemi2013]

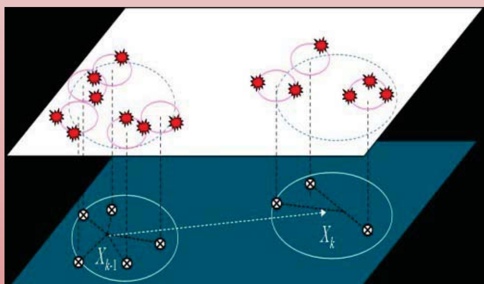
Track before detect (TBD)

- Common in radar data with low signal to noise ratio
- Track the signal before declaring it a target

- Common algorithms
  - Probability Hypothesis Density (PHD) filter [Mahler2003, Pace2011, Vo2013]
  - Probabilistic Multiple Hypothesis Tracker (PMHT) and its variant Histogram – Probabilistic MHT (H-PMHT) [Streit1995, Davey2015]
  - Maximum Likelihood Probabilistic Data Association (ML-PDA) [Willet2011]

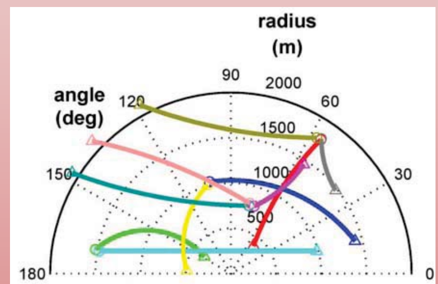
Random Finite Sets-based methods

RFS



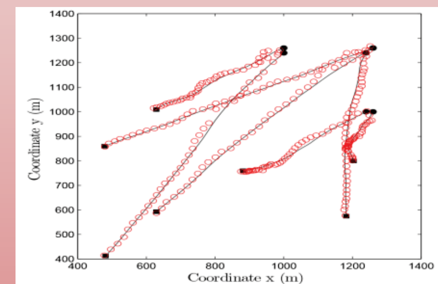
[Mahler2003]

PHD



[Pace2011]

L-RFS / GLMB



[Vo2013]
[Vo2014]
[Papi2015]