Data fusion and multitarget tracking: some interests for military and automotive applications.

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Just a few words about me…

- One year internship
  Munich, Germany
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- Master and PhD degree
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Outlook

1. Military application: convoy detection and tracking
    1. Multi-target tracking, a brief overview
    2. Hybridization of CPHD filter and MHT
    3. Bayesian network for convoy detection
2. Multi-target detection and tracking with uncalibrated aerial videos
    1. Detection
    2. Tracking
3. Automotive applications
    1. Multi-lane detection and tracking

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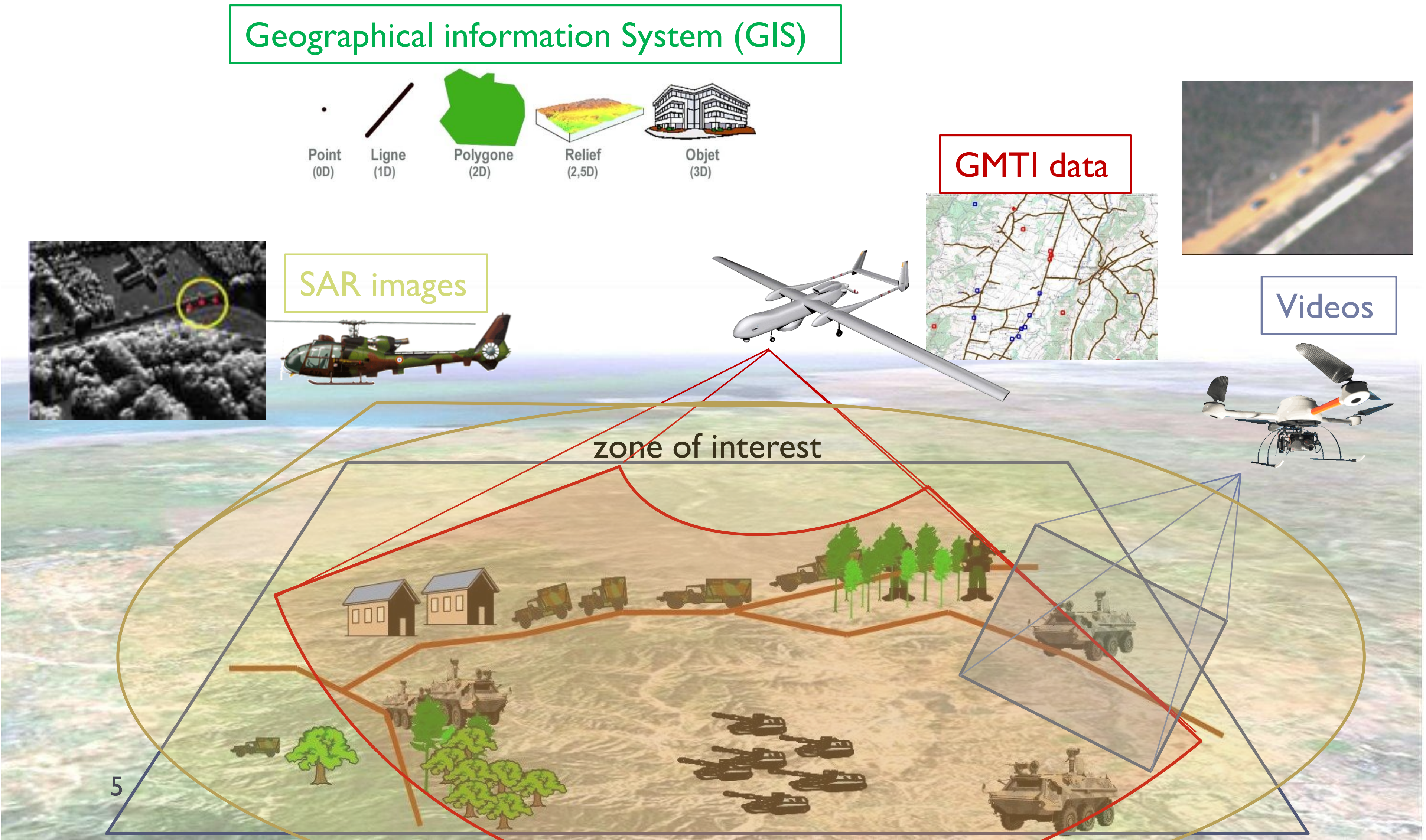
Battlefield surveillance



General problem

- Goal
  - Situation assessment
    - How many targets on the scene ?
    - What is their behavior ?
    - Are they objects of interest ?

Convoy detection

- Methods

- 1st step: Using GMTI sensor to detect agregates

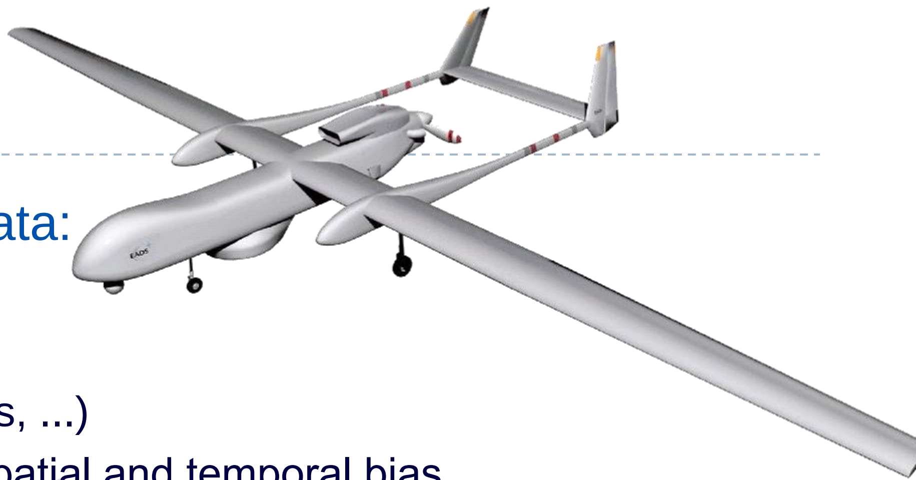
Algorithm weaknesses for closely spaced target tracking

Use a promising algorithm: the PHD filter (Probability Hypothesis Density)

- 2nd step: Integrate other data types to determine if the detected aggregates are convoys or not.

and if so, how many targets are in

GMTI data



- GMTI (Ground Moving Target Indicator) data:
  - High traffic density
  - High maneuverability of ground targets
  - Environment complexity (roads, mountains, ...)
  - Sensor limitations: measurement noise, spatial and temporal bias,…
  - False alarms , P_D<1 and spawned targets

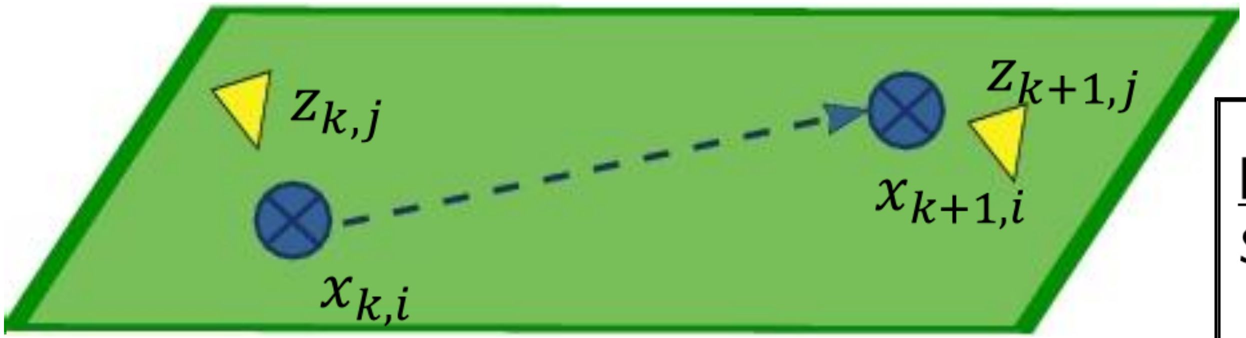
<u>Observations:</u>

$$Z_k = \{z_{k,1}, \dots, z_{k,m_k}\}$$

<u>MTI report:</u>

$$z_{k,i} = [\tilde{x}, \tilde{y}]^T$$

Single object tracking



Real state of a target:

$$x_{k,i} = [x, \dot{x}, y, \dot{y}]^T$$

Model:

State equation

$$x_{k+1,i} = F x_{k,i} + b_{k,i}$$

Observation equation

$$z_{k,j} = H x_{k,i} + w_{k,j}$$

Goal: calculate an estimation

$$\hat{x}_{k|k,i} = E\left[x_{k,i} | Z^k\right]$$

$$\hat{P}_{k|k,i} = E\left[(x_{k,i} - \hat{x}_{k|k,i})(x_{k,i} - \hat{x}_{k|k,i})^T | Z^k\right]$$

solved by Kalman filter equation with linear/Gaussian assumption

Optimal Bayesian Filter: Kalman filter

Propagation of the probability density function (pdf) of x_k

a priori pdf | motion model | previous pdf

Prediction

$$f_{k|k-1}(x_k \mid Z^{k-1}) = \int f_{k|k-1}(x_k \mid x_{k-1})\, f_{k-1|k-1}(x_{k-1} \mid Z^{k-1})\, dx_{k-1}$$

likelihood | *a priori* pdf

Update

$$f_{k|k}(x_k \mid Z^k) = \frac{f_{k|k}(z_k \mid x_k)\, f_{k|k-1}(x_k \mid Z^{k-1})}{f_{k|k}(z_k \mid Z^{k-1})}$$

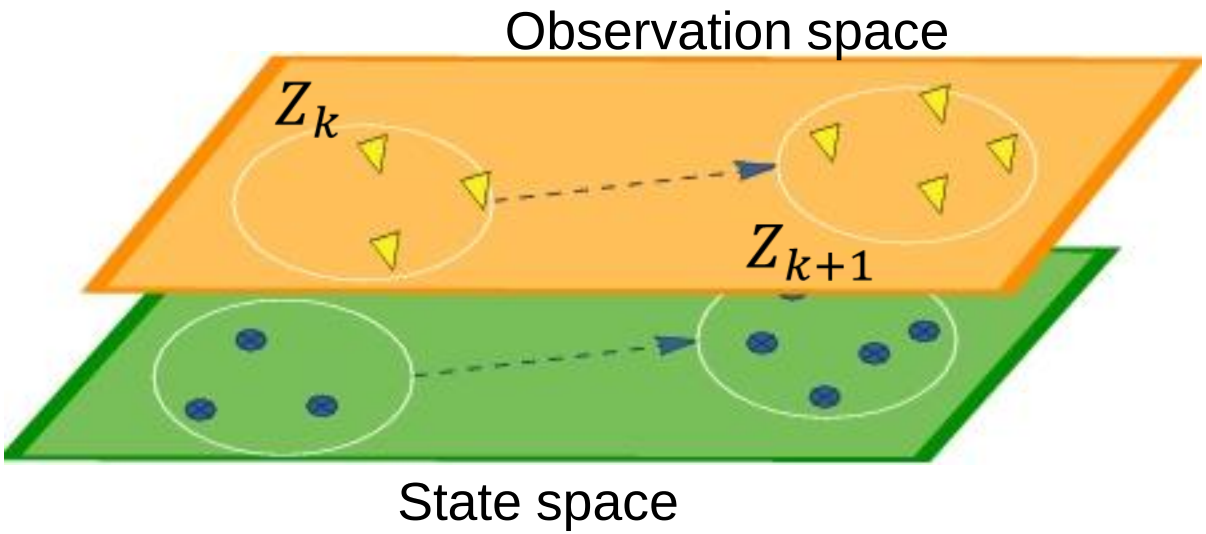
a posteriori pdf | normalization

Estimator

$$\hat{x}_{k|k} = \arg\sup_x \, f_{k|k}(x \mid Z^k)$$

[Mahler01] : *Detecting, tracking and classifying group targets: a unified approach*, Proc. of SPIE Vol. 4380

Multi-target tracking



- Varying number of targets:
  - Birth targets
  - Stationary targets
  - Output of the observation zone

  False alarm

  Non-detection

Goal: calculate an estimation

State: $\hat{X}_{k|k} = \left\{ \hat{x}_{k|k,1}, \dots, \hat{x}_{k|k,\hat{N}_{k|k}} \right\}$

Covariance: $\hat{P}_{k|k} = \left\{ \hat{P}_{k|k,1}, \dots, \hat{P}_{k|k,\hat{N}_{k|k}} \right\}$

Number of targets: $\hat{N}_{k|k}$

Labeling: $\tau_{k,j} = \{ \hat{x}_{k|k,i}, \hat{P}_{k|k,i}, s_{k,i}, \tau_{k-1,j} \}$

solved by MHT, JPDAF, particle filter…
and CPHD filter

Random Finite Set (RFS)

- Target set X_k modeled as a RFS

$$X_k = \left[\bigcup_{\zeta \in X_{k-1}} S_{k|k-1}(\zeta) \right] \cup \left[\bigcup_{\zeta \in X_{k-1}} B_{k|k-1}(\zeta) \right] \cup \sigma_k$$

  - $S_{k|k-1}(\zeta)$: Survival targets between iteration *k* and iteration *k*-1
  - $B_{k|k-1}(\zeta)$: Spawned targets
  - σ_k : Birth targets

- Measurement set Z_k modeled as a RFS

$$Z_k = \left[\bigcup_{x \in X_k} \theta_k(x) \right] \cup \kappa_k$$

  - θ_k : Target originated measurement
  - κ_k : false alarms

Multi-sensor/Multi-target Bayes filter

Propagation of the joint probability density function (jpdf) of RFS X_k

a priori jpdf motion model previous jpdf

Prediction

$$f_{k|k-1}(X_k|Z^{k-1}) = \int f_{k|k-1}(X_k|X_{k-1})\, f_{k-1|k-1}(X_{k-1}|Z^{k-1})\, dX_{k-1}$$

measurement likelihood *a priori* jpdf

Update

$$f_{k|k}(X_k|Z^k) = \frac{f_{k|k}(Z_k|X_k)\, f_{k|k-1}(X_k|Z^{k-1})}{f_{k|k}(Z_k|Z^{k-1})}$$

a posteriori jpdf normalization

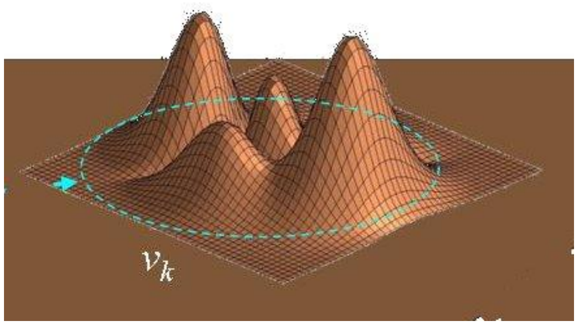
Estimator

$$\hat{X}_{k|k} = \arg\sup_X f_{k|k}(X|Z^k)$$

[Mahler03] : *Multitarget Bayes Filtering via First-Order Multitarget Moments*, IEEE AES, Vol. 39, No 4

PHD definition

- v_k : first-order statistical moment of the multitarget posterior, also called intensity function or Probability Hypothesis Density



$$\mathbf{E}\left[\left| X \cup S \right| \right] = \int_S v_k(x)\,dx$$

PHD filter principle

- Prediction

$$v_{k|k-1}(\mathrm{x}) = \left(\int P_s(\zeta).\, f_{k|k-1}(x|\zeta)\, v_{k-1}(\zeta)\, d\zeta\right) + \gamma_k(\mathrm{x})$$

- P_s : survival probability between iteration *k* and iteration *k-1*
- $f_{k|k-1}(.|\zeta)$: transition function knowing the previous state ζ
- γ_k : birth intensity

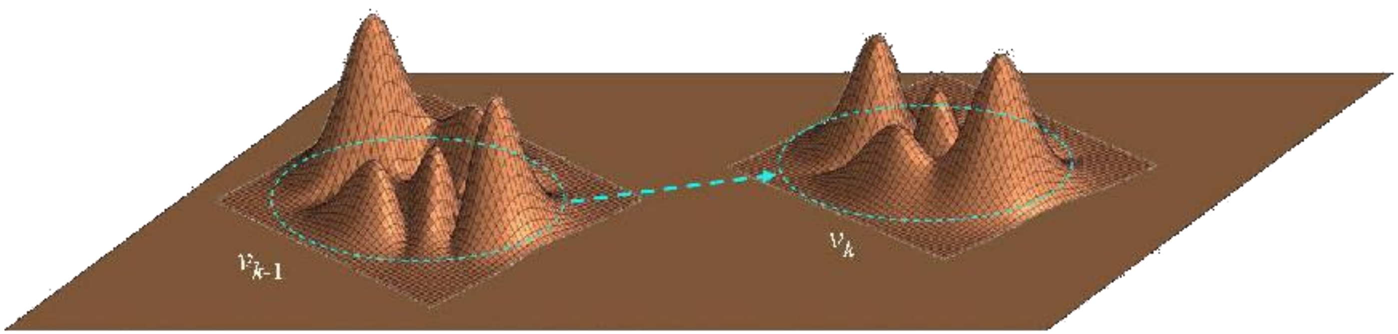
- Estimation

$$v_k(x) = (1 - P_d)\, v_{k|k-1}(\mathrm{x}) + \sum_{z \in Z_k} \frac{P_d \,.\, \mathrm{g}(z|x).\, v_{k|k-1}(\mathrm{x})}{\kappa_k(z) + \int P_d\, \mathrm{g}(z|\zeta).\, v_{k|k-1}(\zeta)\, d\zeta}$$

- P_d : detection probability
- $\mathrm{g}(z|x)$: measurement likelihood
- κ_k : clutter intensity

Several implementation

- Representation of the intensity function v_k
  - Particle PHD
  - Gaussian Mixture PHD (GM-PHD)
  - Gaussian Mixture Cardinalized PHD (GM-CPHD)



- [Vo06] : *Analytical implementation of the Gaussian Mixture Probability Hypothesis Density Filter*, IEEE SP, 2006

Le Cardinalized PHD: principle

- the number of targets is considered as a random variable p
- the corresponding pdf is conjointly propagated over time

Sum of hypotheses for the *n* targets to be

(*n-j*) birth   *l* survival   *(l-j)*non survival

Prediction

$$\forall n \in \mathbb{N}^*, p_{k|k-1}(n) = \sum_{j=0}^{n} p_{\Gamma,k}(n-j) \sum_{l=j}^{\infty} C_j^l p_{k-1}(l) P_s^j (1-P_s)^{(l-j)}$$

Measurement likelihood   *a priori* pdf

Update

$$p_{k|k}(n) = \frac{\mathcal{L}(Z_k|n)}{\mathcal{L}(Z_k)} p_{k|k-1}(n)$$

a posteriori pdf

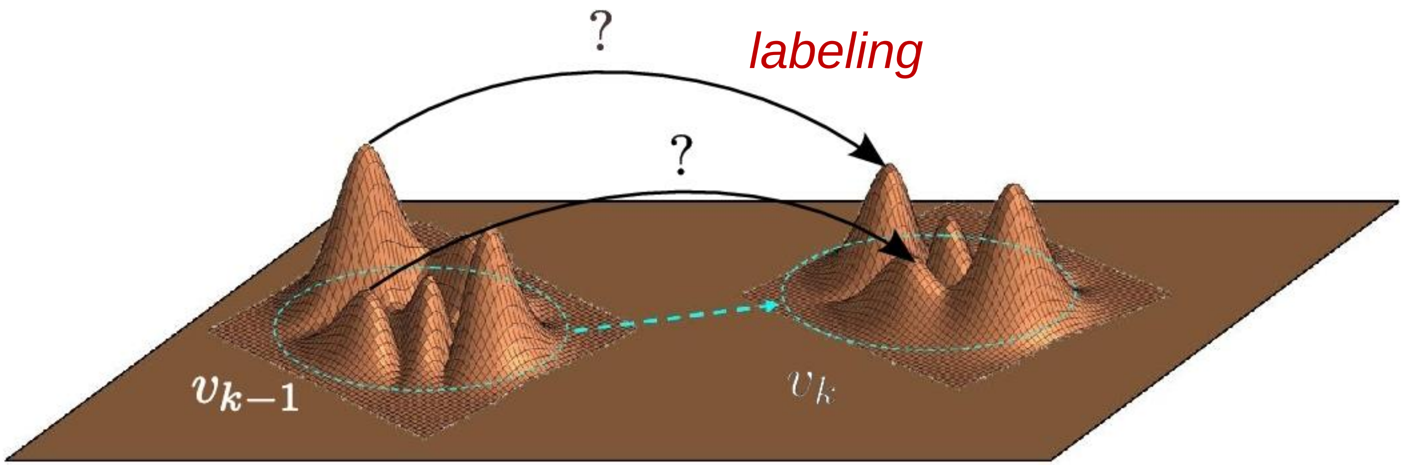
normalization

Estimator

$$\hat{N}_{k|k} = \arg\sup_{n} p_{k|k}(n) \qquad \hat{N}_k = \sum_{n=1}^{\infty} n p_k(n)$$

[Mahler07] : *PHD filters of higher order in target number*, IEEE AES, 2007

Labeling



$\hat{N}_{k-1|k-1}$ $\hat{N}_{k|k}$

Labeled GM-CPHD (1/2)

Principle

- $\mathbf{G}_k$: Gaussian set of size $N_k^{\mathbf{G}}$

weight state covariance

$$\mathbf{G}_k = \left\{ w_{k,i},\, m_{k,i},\, P_{k,i} \right\}_{i \in \left\{1,\ldots,N_k^{\mathbf{G}}\right\}}$$

- $\mathbf{T}_k$: track set of size $\hat{N}_{k|k}$ describing the target trajectory

$$\mathbf{T}_k = \left\{ \hat{x}_{k,i},\, P_{k,i},\, s_{k,i},\, \mathbf{T}_{k-1,j} \right\}_{i \in \left\{1,\ldots,\hat{N}_{k|k}\right\}}$$

state covariance score

Goal

Evaluate the track-to-Gaussian association matrix $\mathbf{A}_k$ of size $\left(\hat{N}_{k|k} \times N_k^{\mathbf{G}}\right)$

$$\mathbf{A}_k(m,n) = \begin{cases} 1 & \text{If the Gaussian component } n \text{ is associated to the track } m \\ 0 & \text{otherwise} \end{cases}$$

Labeled GMCPHD (2/2)

- ## Means
  - Maximization of the weight matrix $\mathbf{W}_k$

$$\mathbf{W}_k = \begin{cases} w_{k,n} & \text{If the Gaussian } n \text{ can be associated to the predicted track } m \\ 0 & \text{Otherwise} \end{cases}$$

$$\mathbf{W}_k = \underbrace{\begin{bmatrix} 0.9 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.6 \\ 0 & 0.7 & 0.1 & 0 \end{bmatrix}}_{\text{4 Gaussian components}} \left.\vphantom{\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}}\right\} \text{3 tracks}$$

  - Minimization of the cost matrix $\mathbf{C}_k$

$$\mathbf{C}_k = \begin{cases} c(m,n) & \text{If the Gaussian } n \text{ can be associated to the predicted track } m \\ 0 & \text{Otherwise} \end{cases}$$

$$\mathbf{W}_k = \begin{bmatrix} 0.9 & 0 & 0 & 0 \\ 0 & 0.7 & 0.6 & 0.1 \\ 0 & 0.7 & 0.6 & 0 \end{bmatrix}$$

$$C_k = \begin{bmatrix} -4.55 & 0 & 0 & 0 \\ 0 & -4.83 & -2.85 & -0.52 \\ 0 & -3.67 & -5.18 & 0 \end{bmatrix}$$

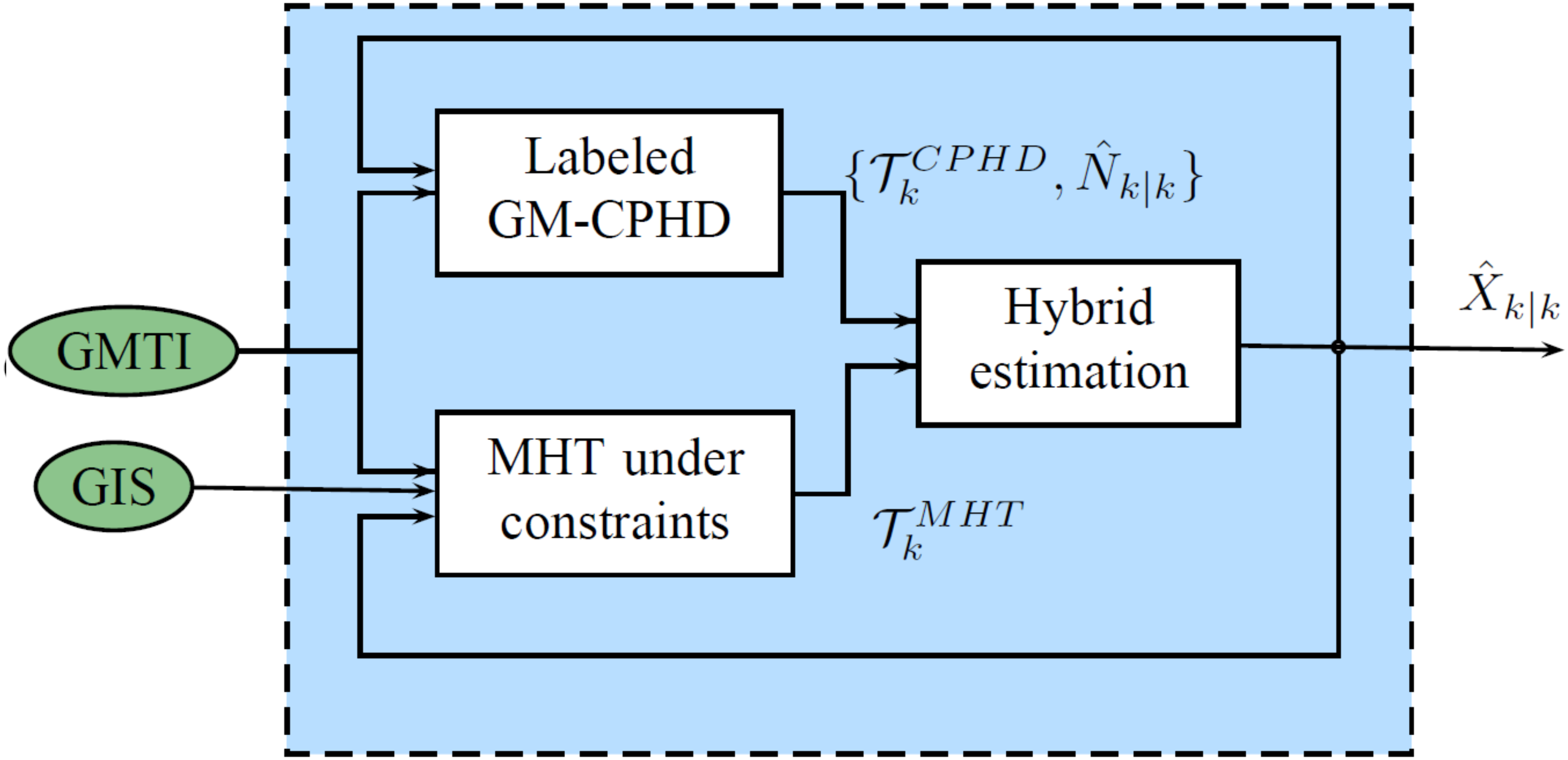
Comparison between the IMM-MHT and the GMCPHD filter

	IMM-MHT	GMCPHD	Hybridization
Target position estimation	++	+	++
Target velocity estimation	++	-	++
Number of targets estimation	-	++	++
Computational complexity	+	++	+

Creation of a hybrid algorithm which would combine the advantages of both of them

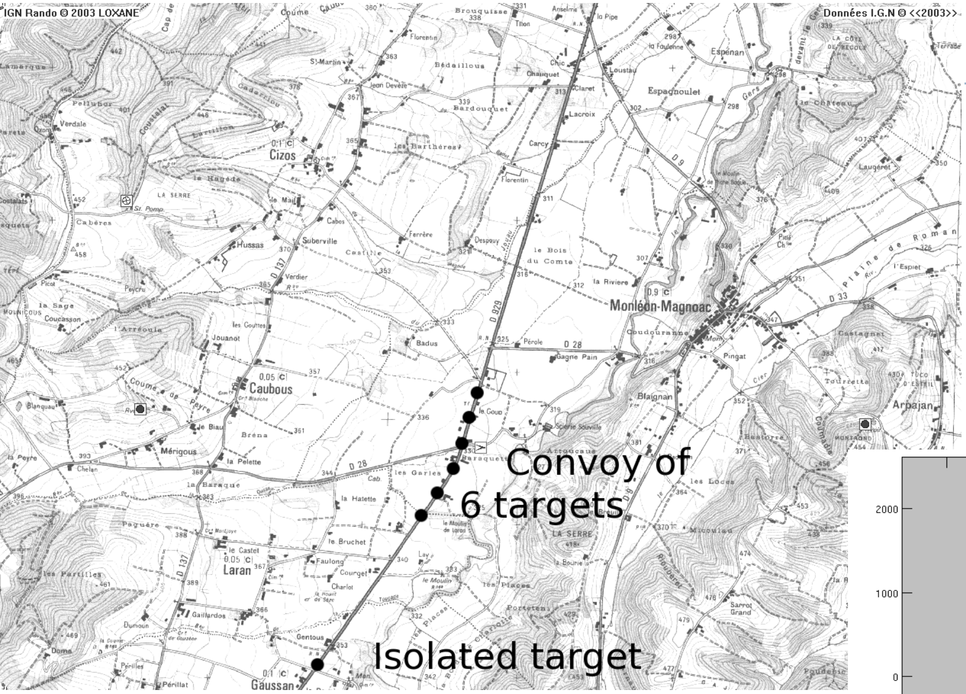
- IMM-MHT: Interacting Multiple Model – Multiple Hypothesis Tracker
- GMCPHD: Gaussian Mixture Cardinalized Probability Hypothesis Density

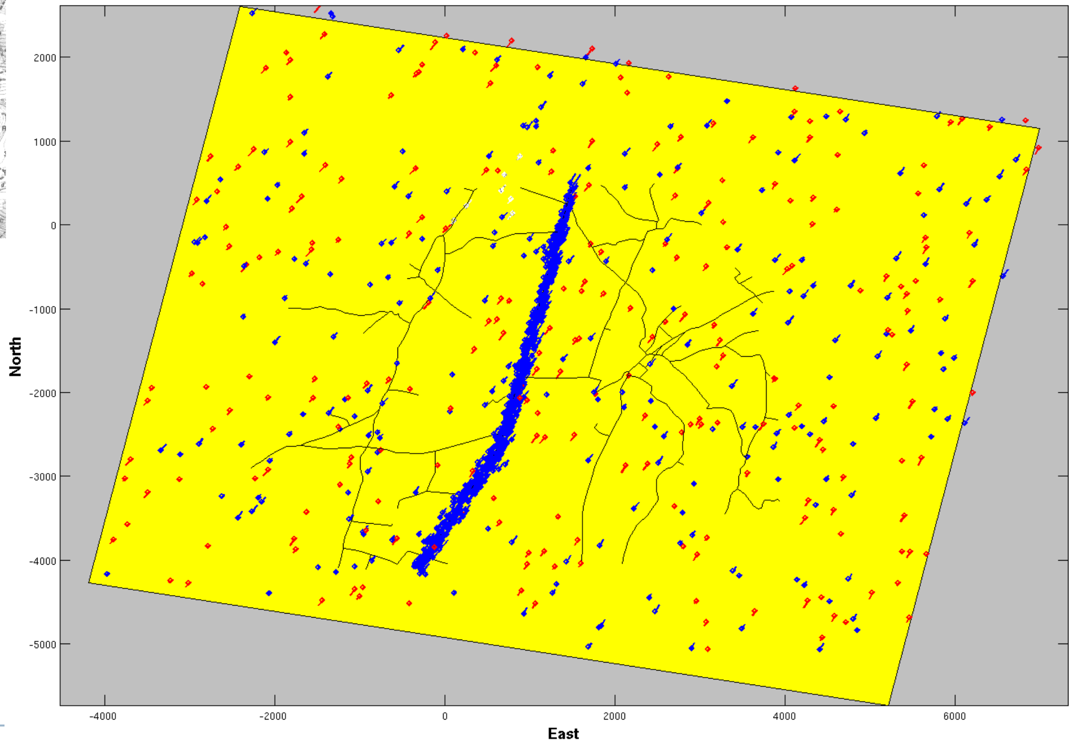
Hybridization



[Pollard11] : E. Pollard, B. Pannetier, M. Rombaut, "Hybrid algorithms for Multitarget tracking using the MHT and the GMCPHD", *IEEE Aerospace and Electronic Systems*

Scenario

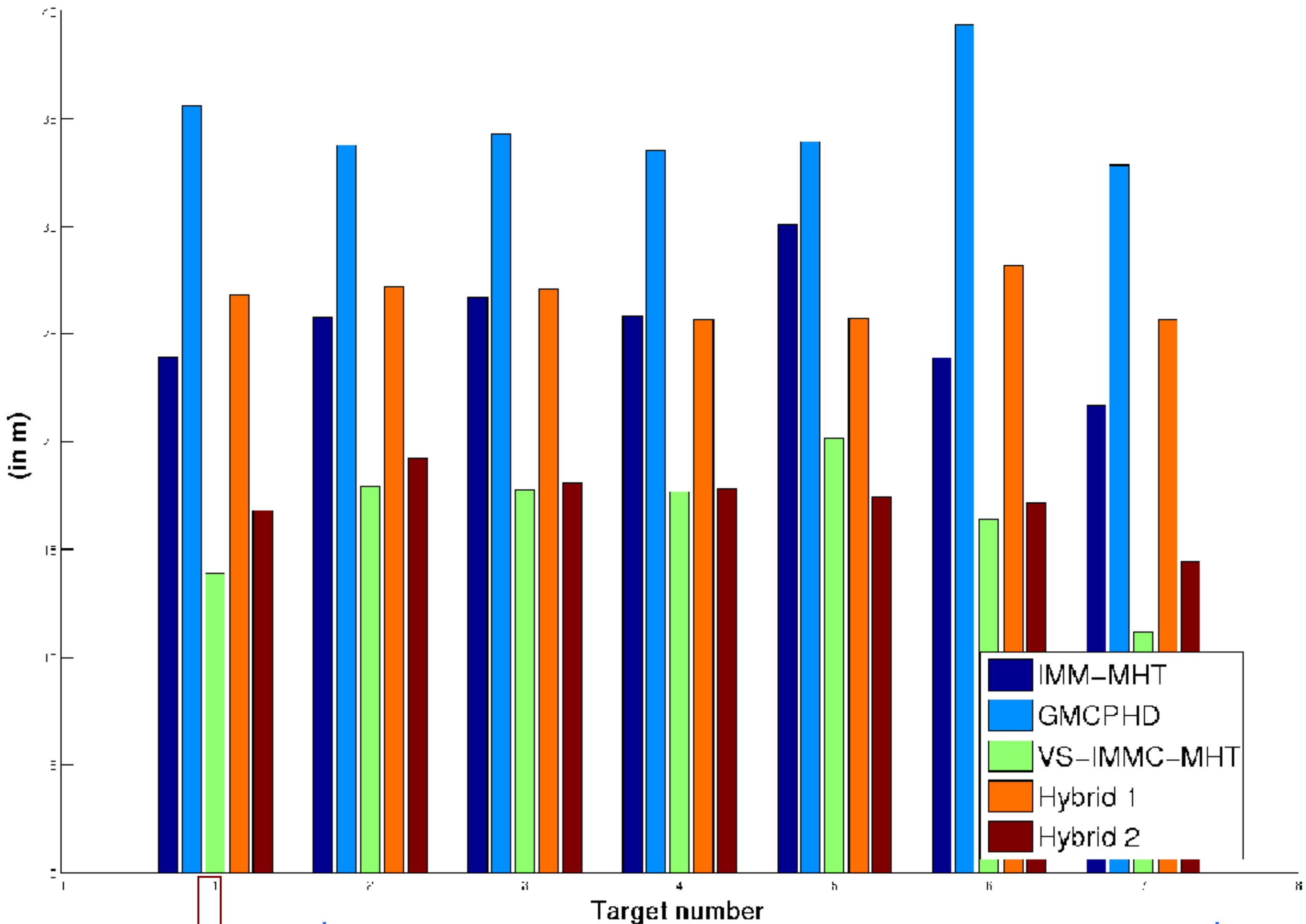




Convoy velocity: 10m/s

Isolated target velocity: 15m/s

Root Mean Square Error in position

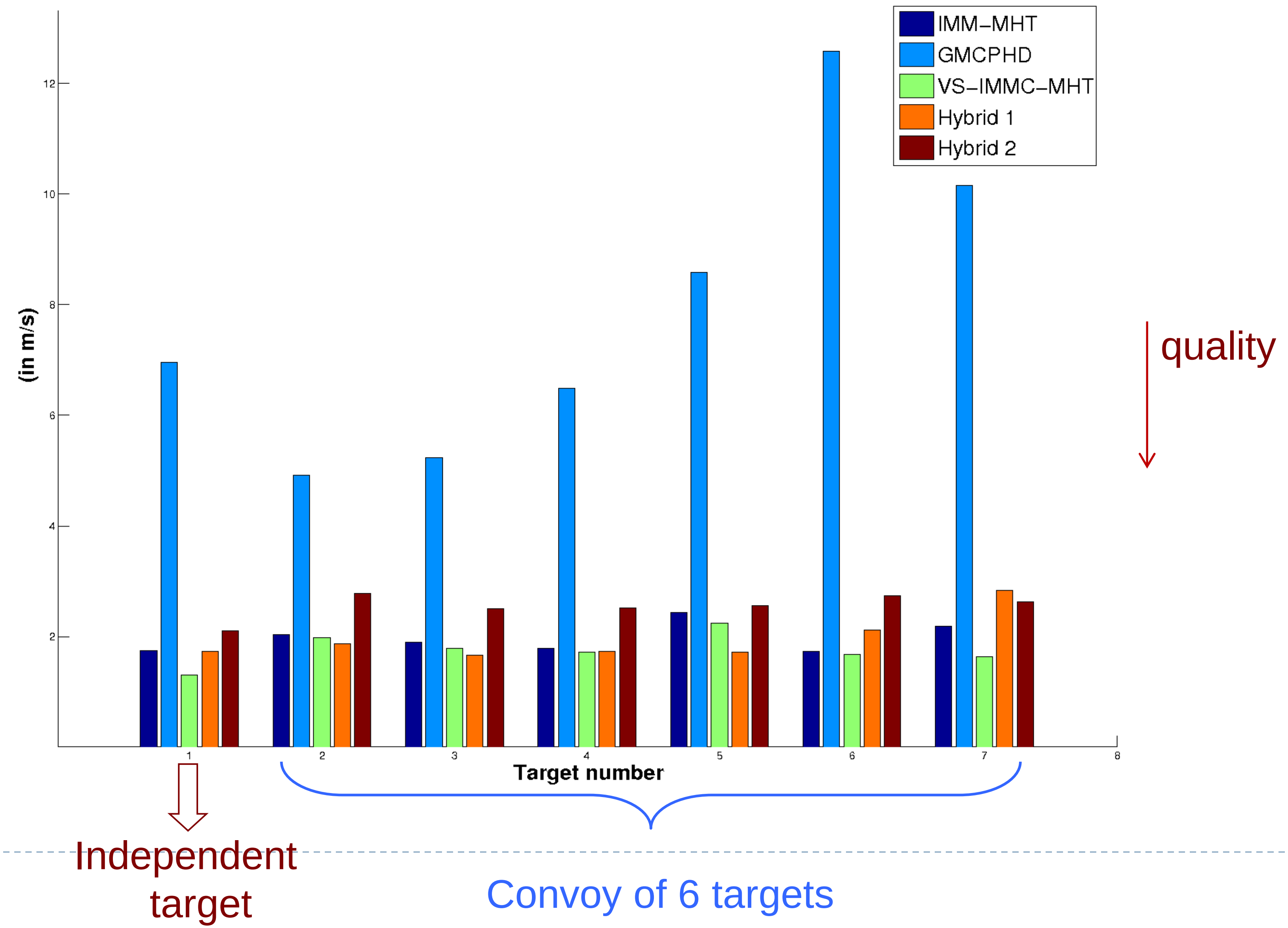


quality

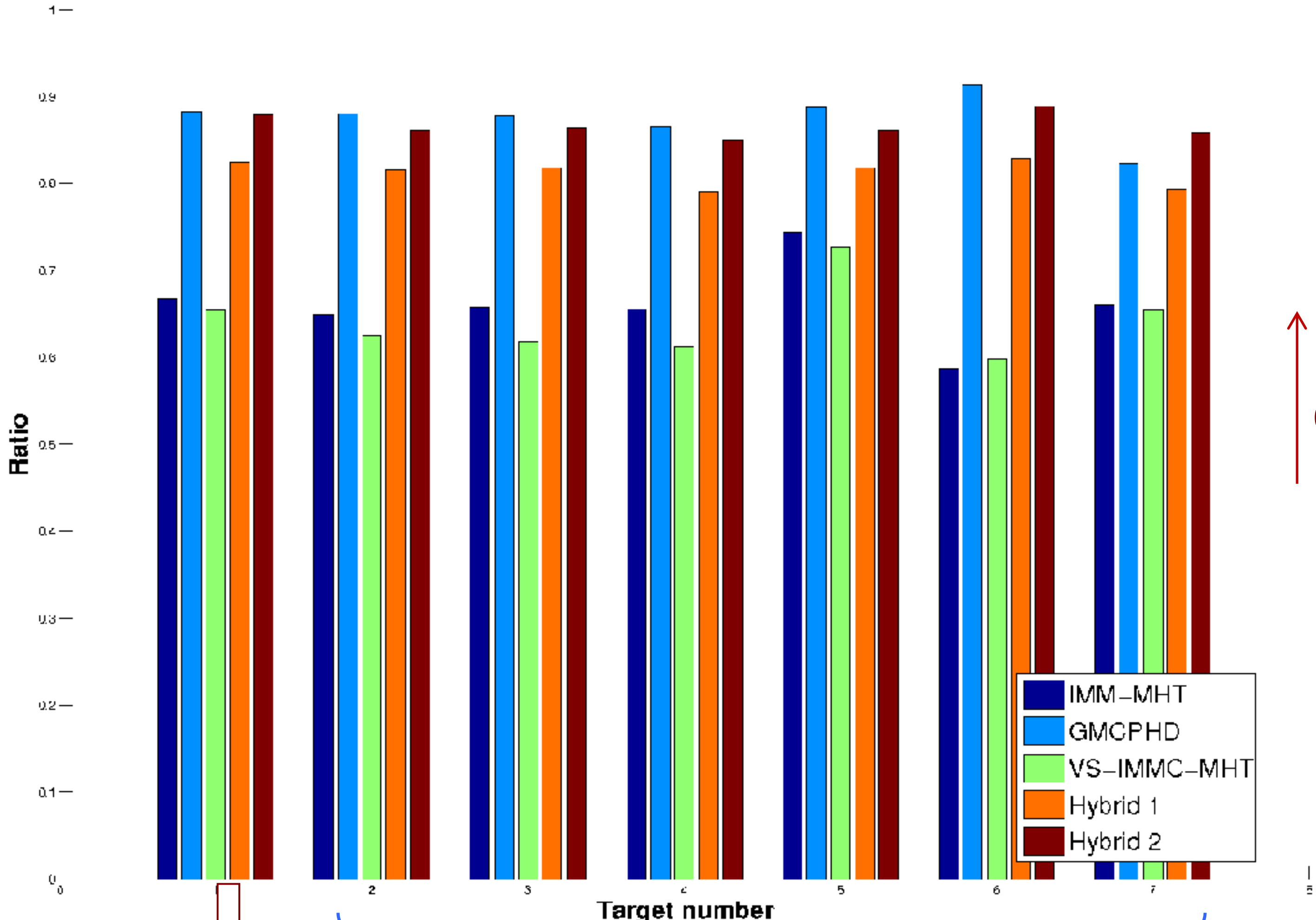
Independent target

Convoy of 6 targets

Root Mean Square Error in velocity



Track length ratio



quality

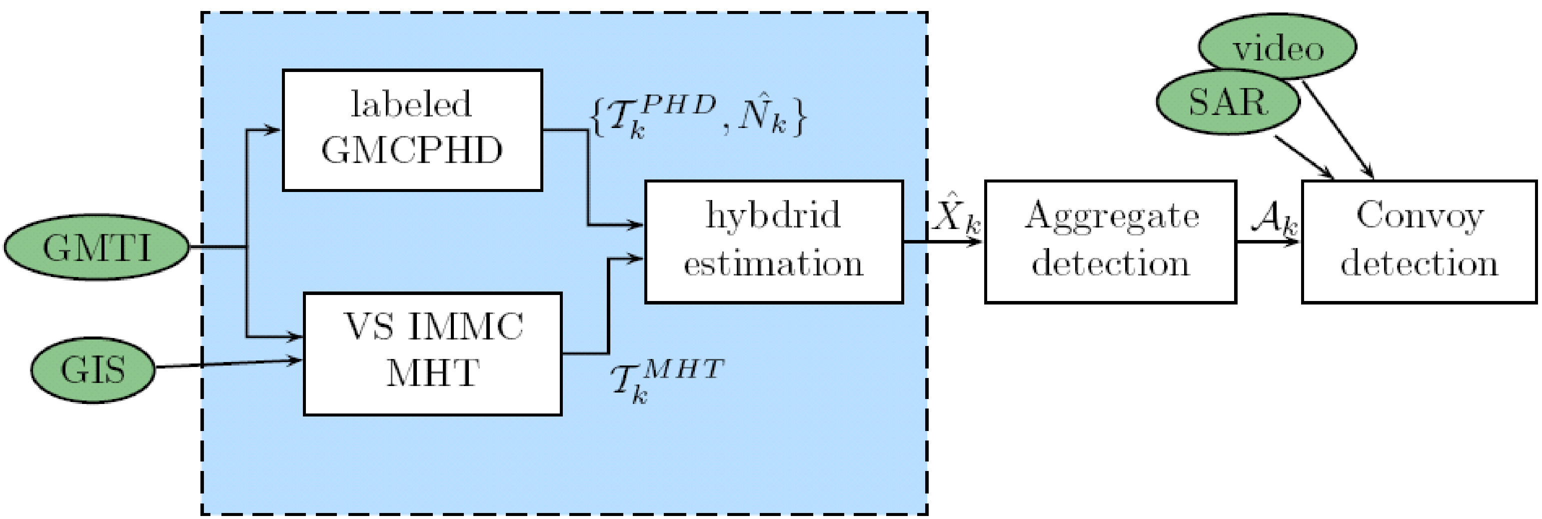
Independent target

Convoy of 6 targets

A convoy detection process

- Elaboration of a new algorithm combining the advantages of the GMCPHD and the IMM-MHT with road constraints
  - No performance drop when targets are close together

Aggregate detection



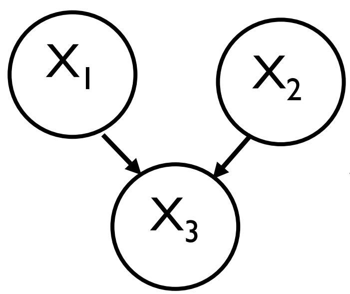
VS-IMMC-MHT / GMCPHD hybridization

Convoy: definition and analysis

- Convoy definition
  - Number of targets > 2
  - Low and constant velocity
  - Military type
  - Stay on sight
  - On the road

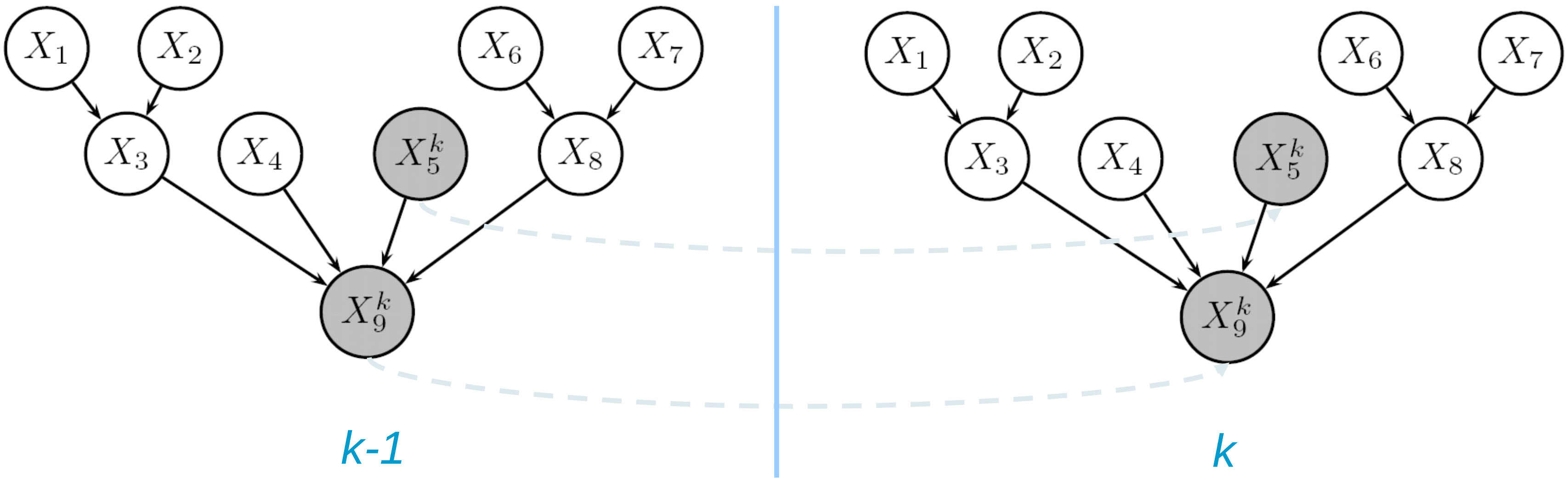
Dynamic Bayesian Network

- System analyze
  - Asynchronous data
  - Heterogeneous data
  - Random variables
  - Missing data
  - Temporal evolution



$$P(X_1, X_2, X_3) = \prod_{i=1}^{3} P(X_i \mid Pa(X_i))$$

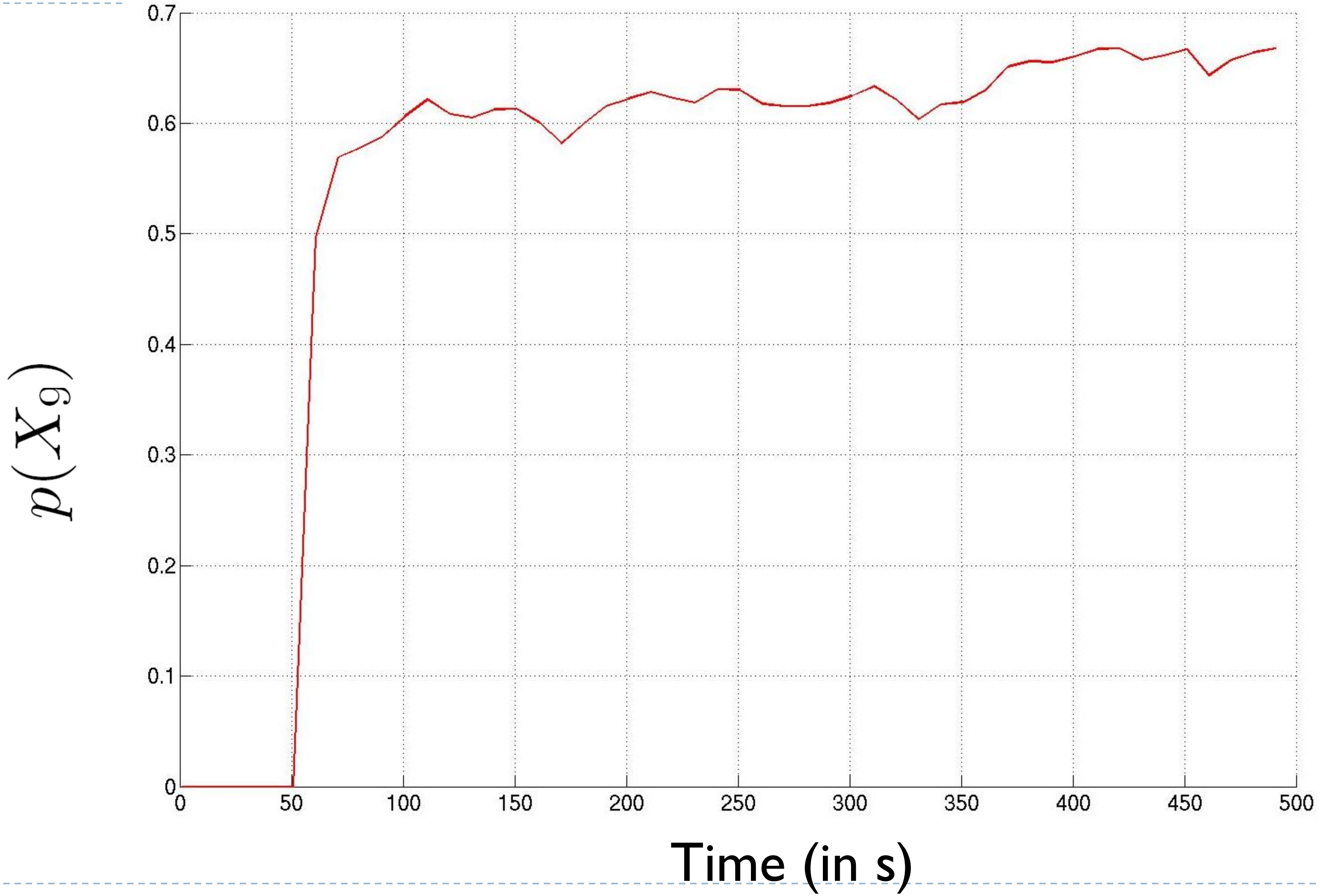
Convoy modeling by using Dynamic Bayesian Network



X_1: Velocity < 80km/h $\{yes, no\}$
X_2: Constant velocity $\{yes, no\}$
X_3: Velocity criteria $\{yes, no\}$
X_4: On the road $\{yes, no\}$
X_5^k: Military vehicles $\{yes, no\}$
X_6: Constant distance between vehicles $\{yes, no\}$
X_7: Constant convoy length over time $\{yes, no\}$
X_8: Distance criteria $\{yes, no\}$
X_9^k: Convoy $\{yes, no\}$

[Pollard09a] : E. Pollard, B. Pannetier, M. Rombaut, "*Convoy detection processing by using the hybrid algorithm (GMCPHD/VS-IMMC-MHT) and Dynamic Bayesian Networks*", Fusion 2009, Seattle

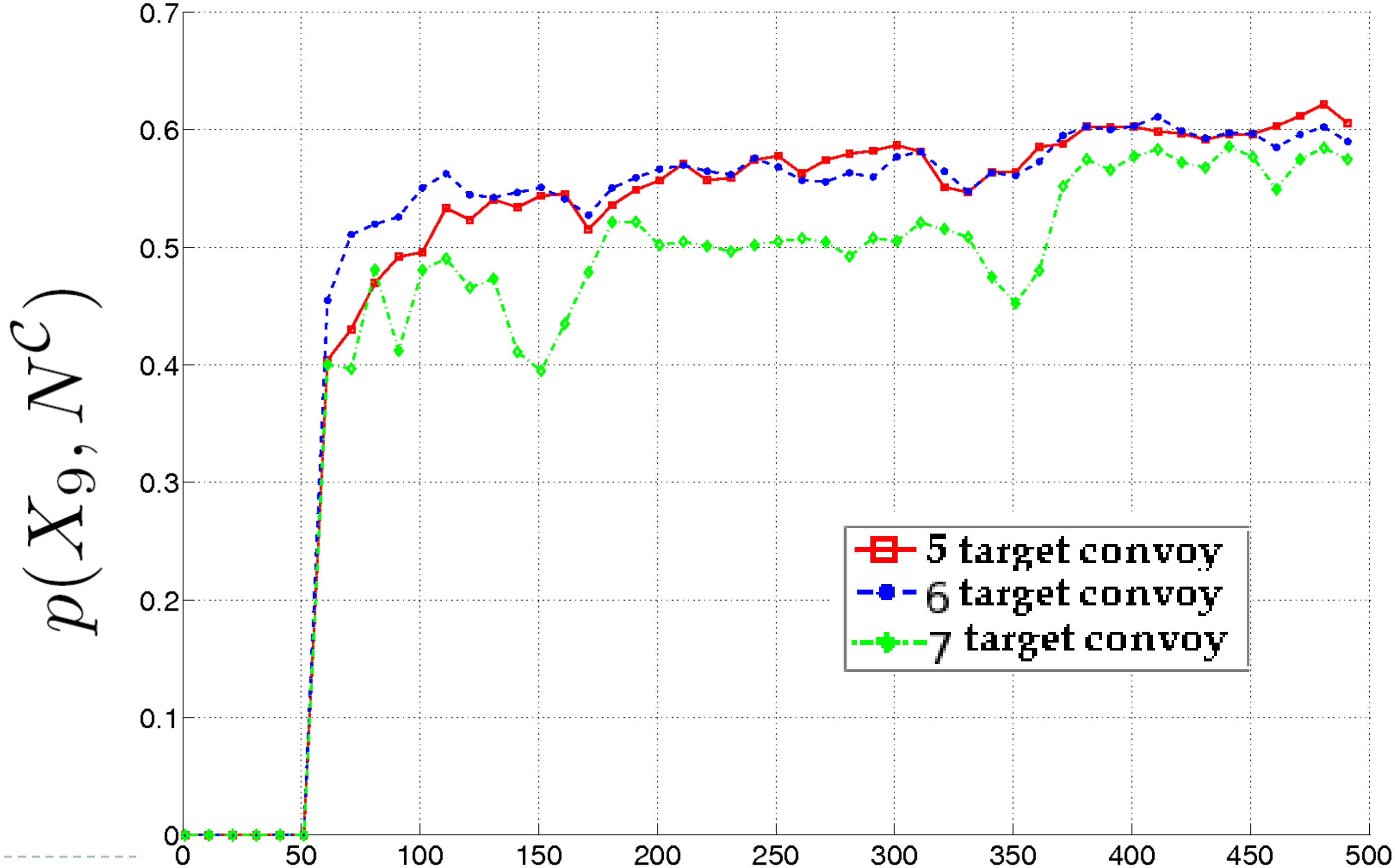
Convoy probablity



Number of target estimation

$$N^k = \{N(1), \ldots, N(k)\}$$

N^C : set of unique value of N^k



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   1. Multi-lane detection and tracking
   2. Ego-localisation by fusing GPS and proprioceptive data

General problem

- Detection
  - Camera motion
  - Parallax effects with urban objects
  - Low image parameters
  - Unknown camera parameters
- Tracking
  - Extended targets
  - Probability of detection <1
  - Hidden zone in urban areas
  - Spawned targets
  - High false alarm rate

[Pollard09b]: E. Pollard, A. Plyer, B. Pannetier, F. Champagnat, G. Lebesnerais, “*GM-PHD Filters for Multi-Object Tracking in Uncalibrated Aerial Videos*”, Fusion 2009, Seattle

Image motion decomposition

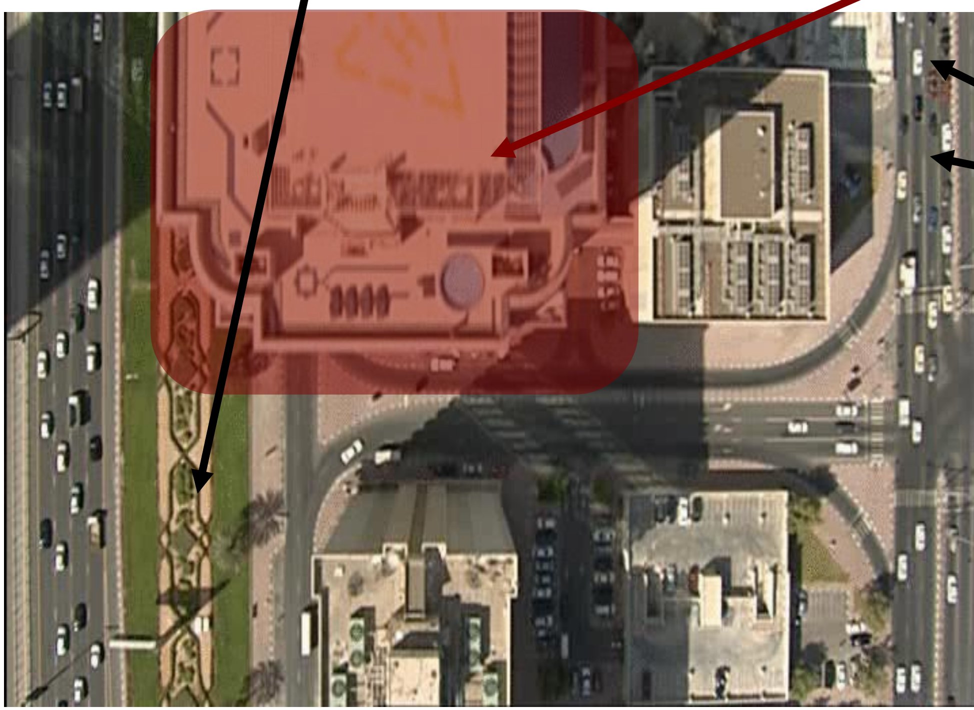
Image motion = ground plane motion

Optical flow algorithm

parametric registration (homography)

+ parallaxe motion

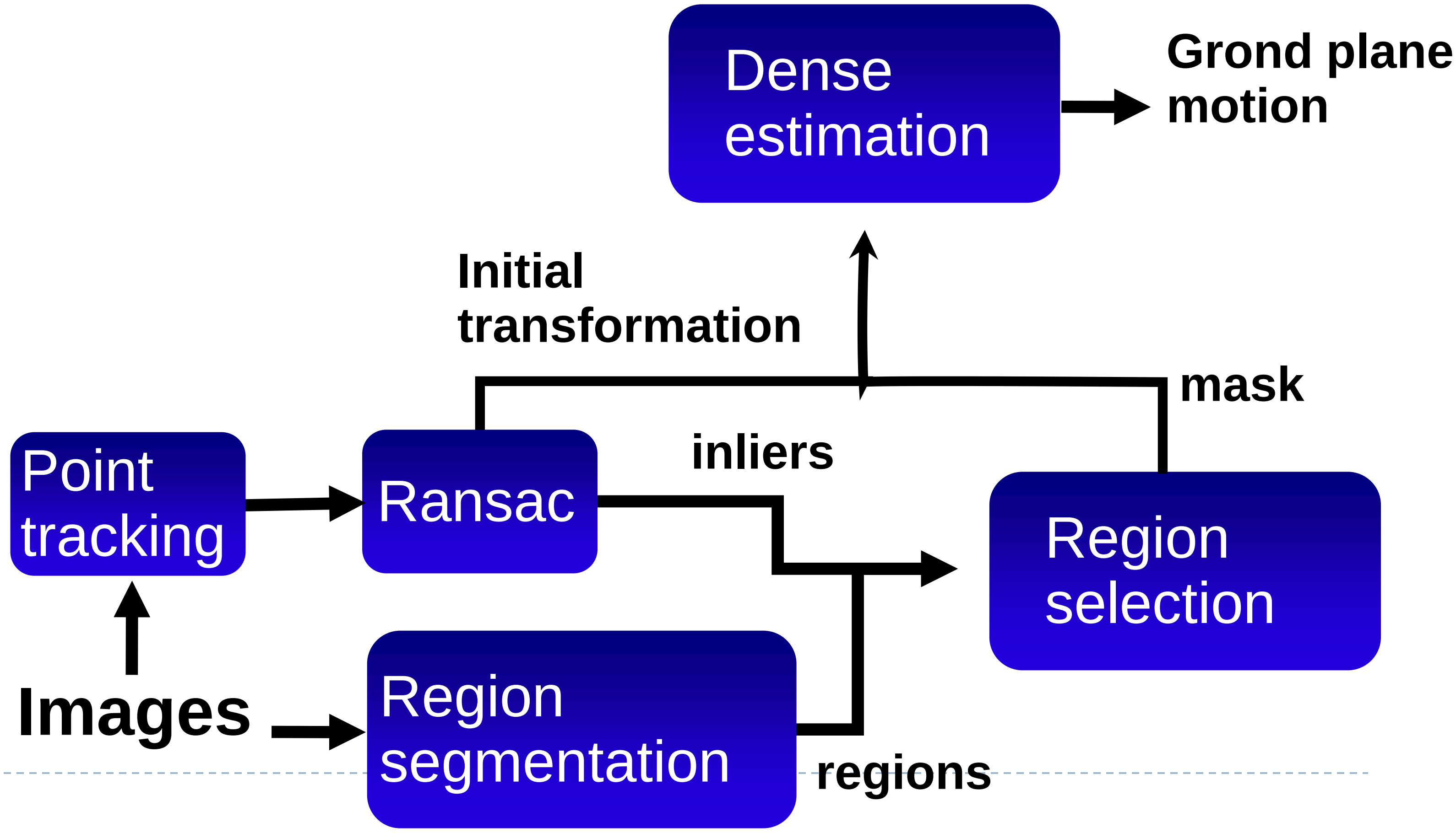
filtered using size requirements



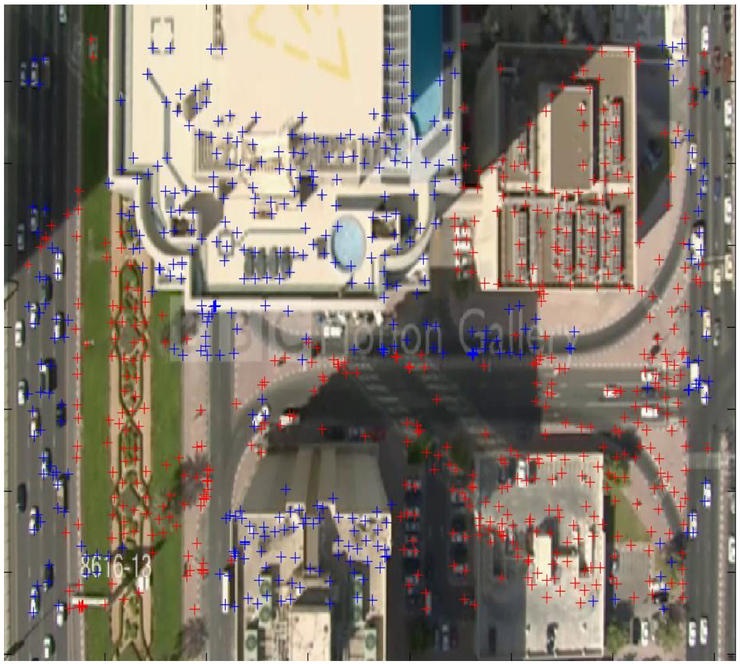
+ moving object motion

residuals

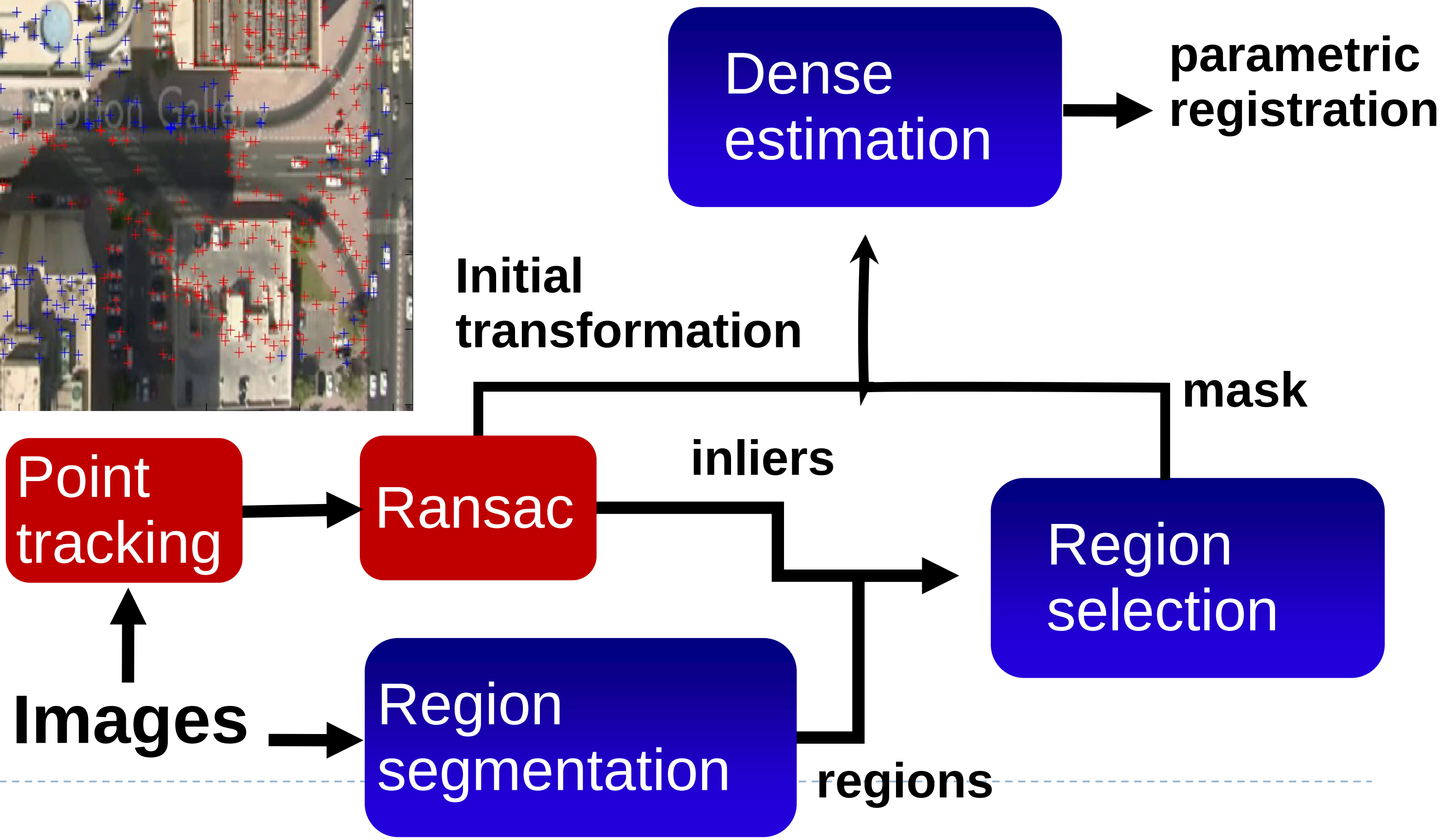
Ground plane motion (1/3)



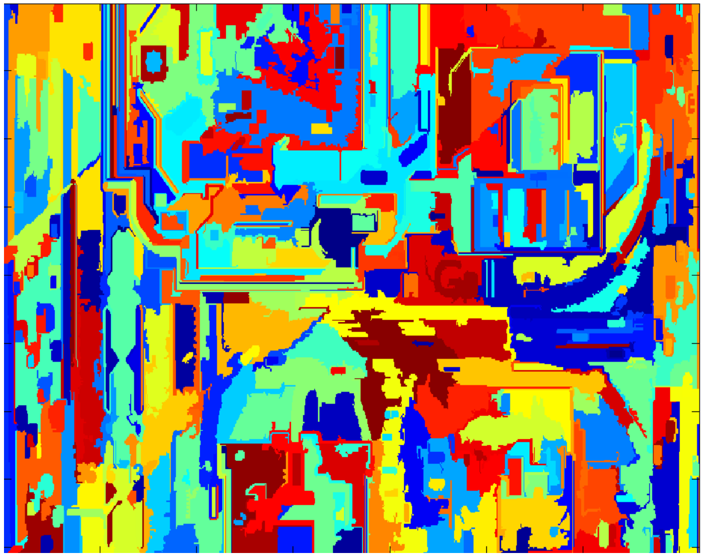
Ground plane motion (2/3)

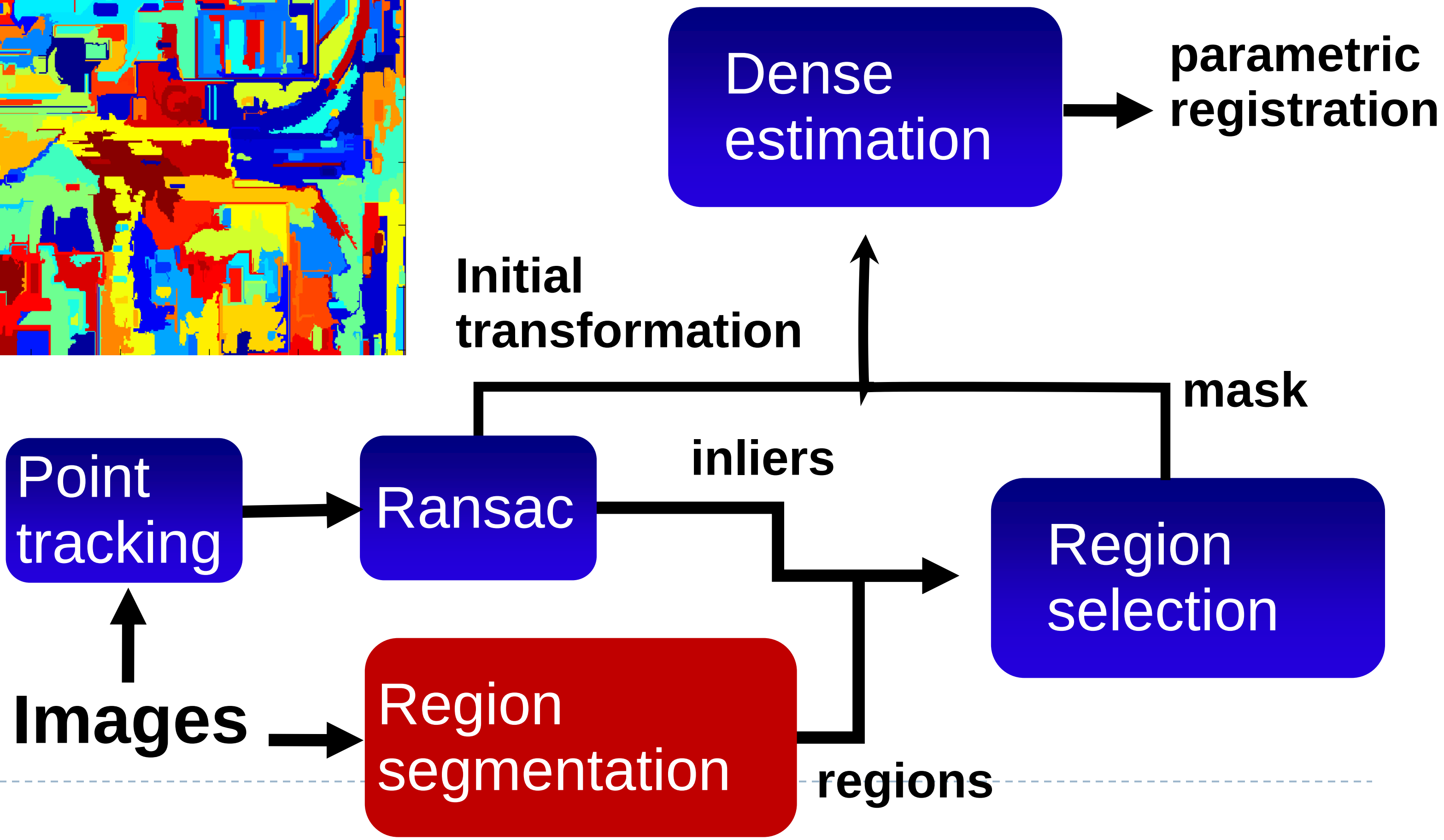


[FOLKI]: G. Le Besnerais, F. Champagnat, “Dense optical flow estimation by iterative local window registration”, in ICIP’05, IEEE, vol. 1, p. I-137-140

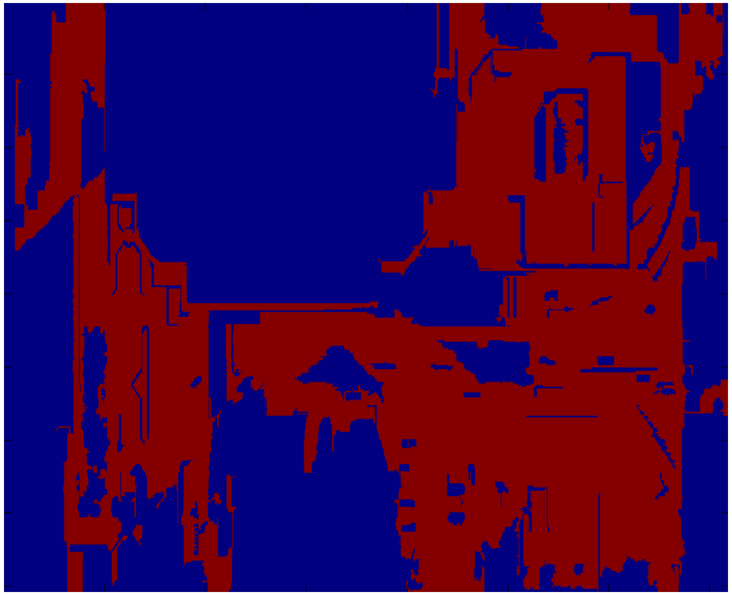


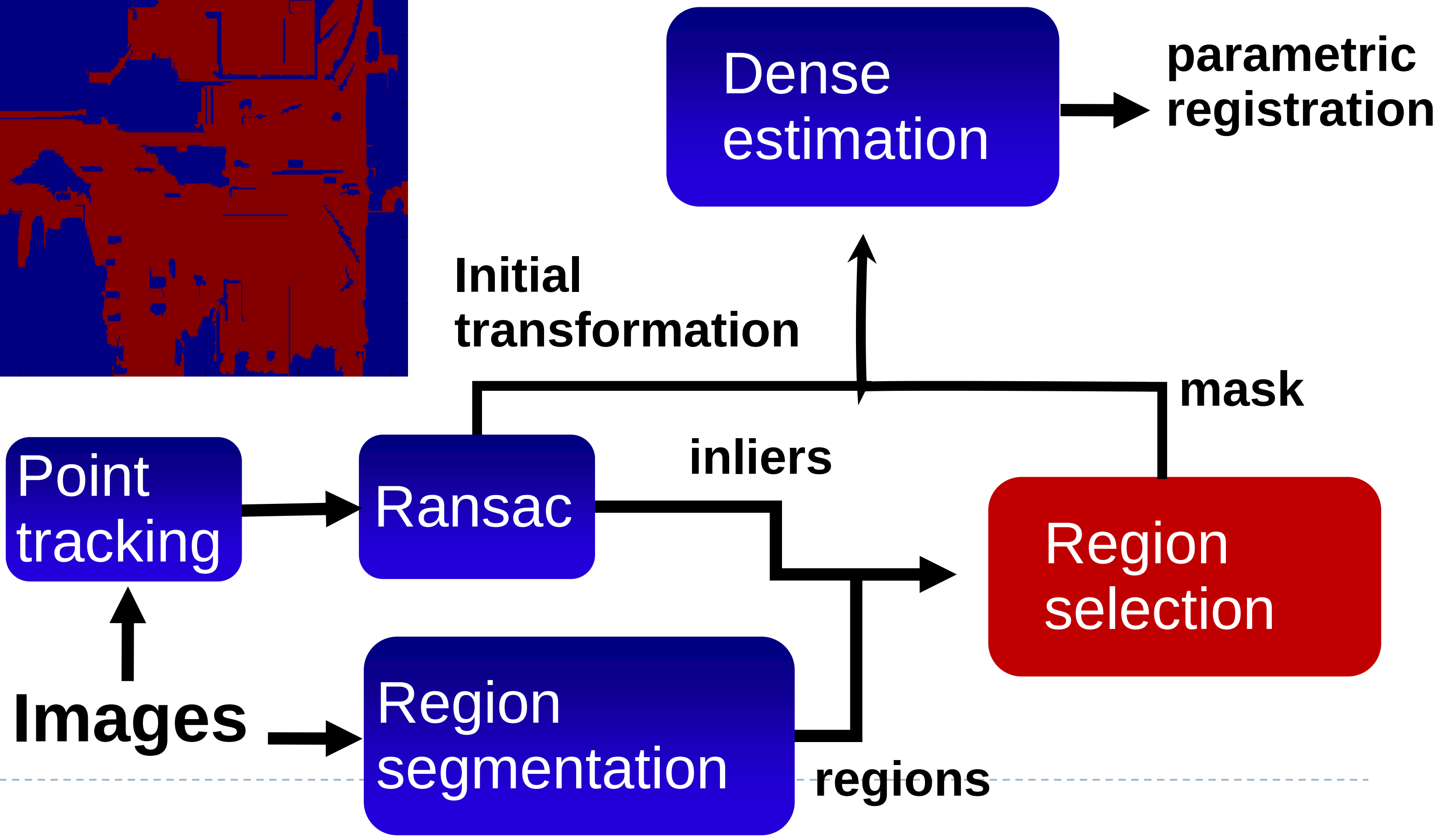
Ground plane motion (3/3)





Ground plane motion (2/3)





Postprocessing

Selection of moving objects

- Edge detection: select region with high density of edges
- Morphological processing: regularize region shape
- Final selection on area (use prior information on object’s size)

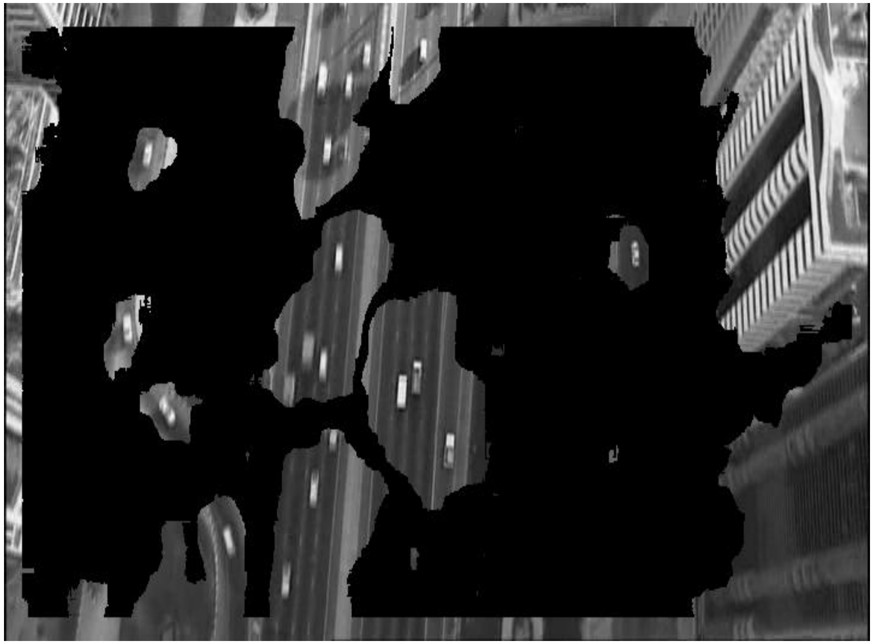
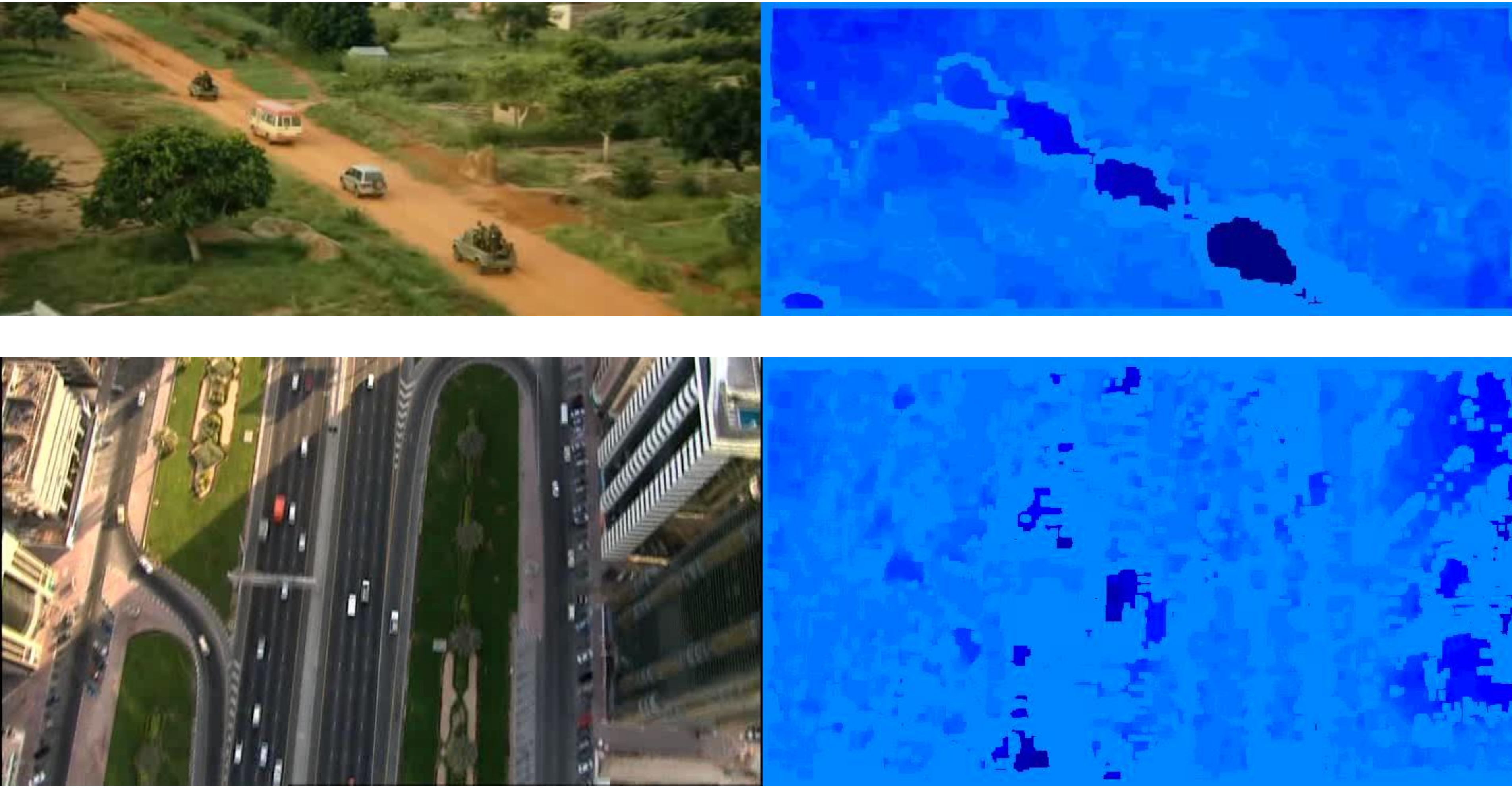


Image segmentation based on the norm of the residual motion

After object selection

Detection results



GM-CPHD tracking

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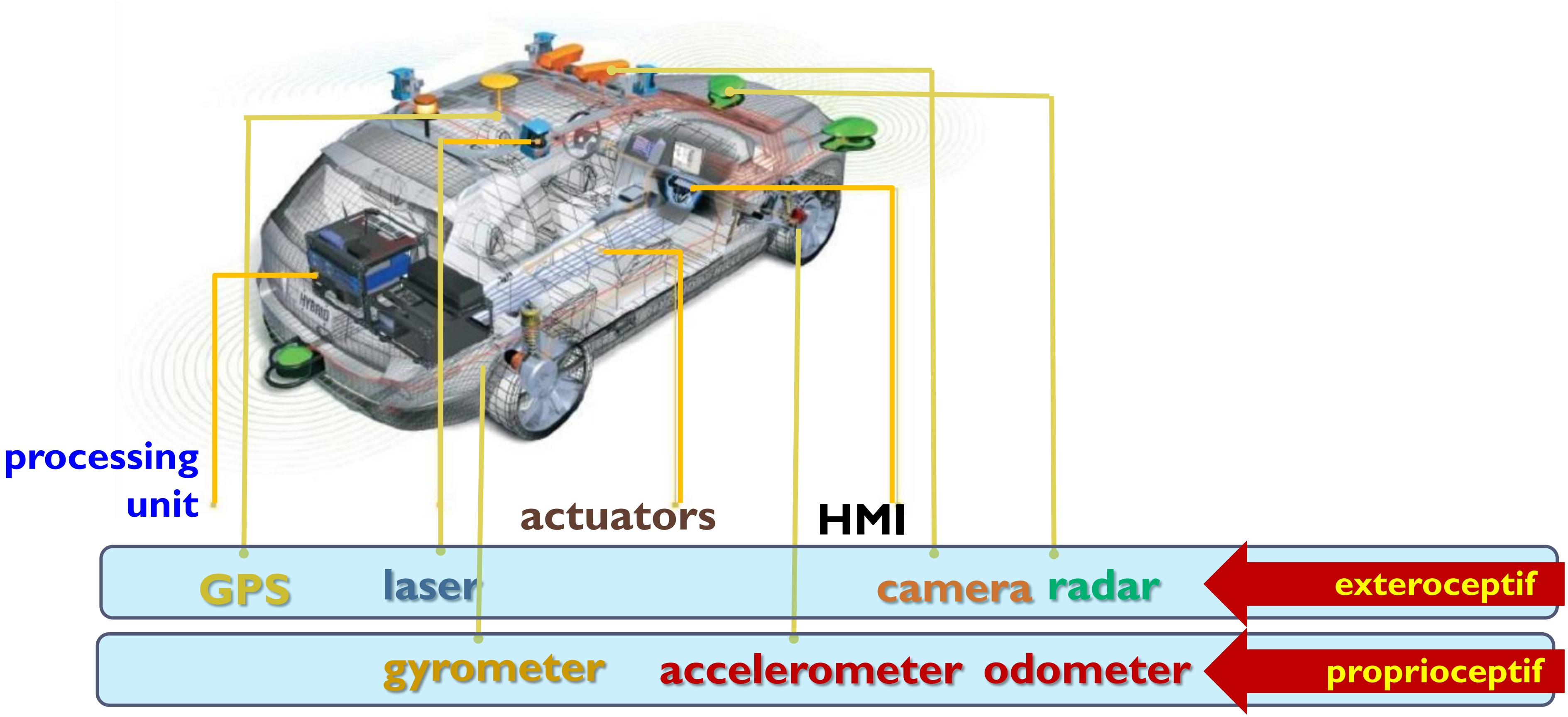
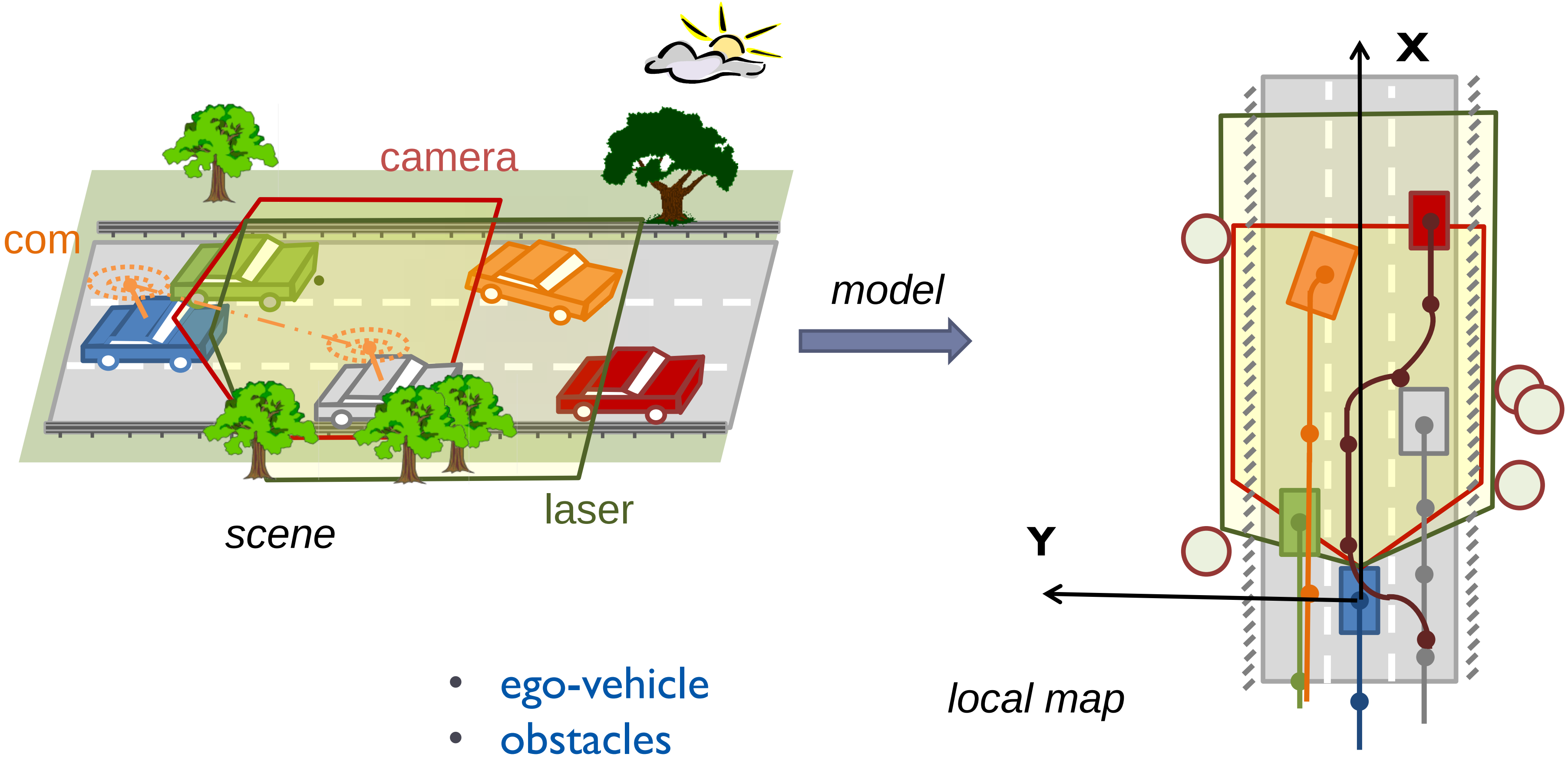
Intelligent vehicle



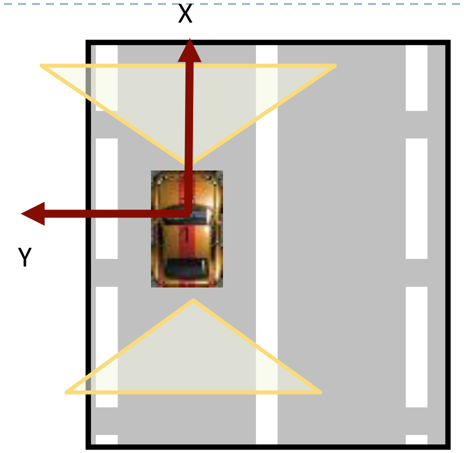
Situation assessment



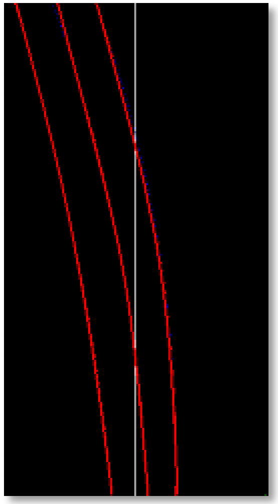
- ego-vehicle
- obstacles
- environment
  - marking lanes

Goals

- Multi-camera system



Multi lane detection

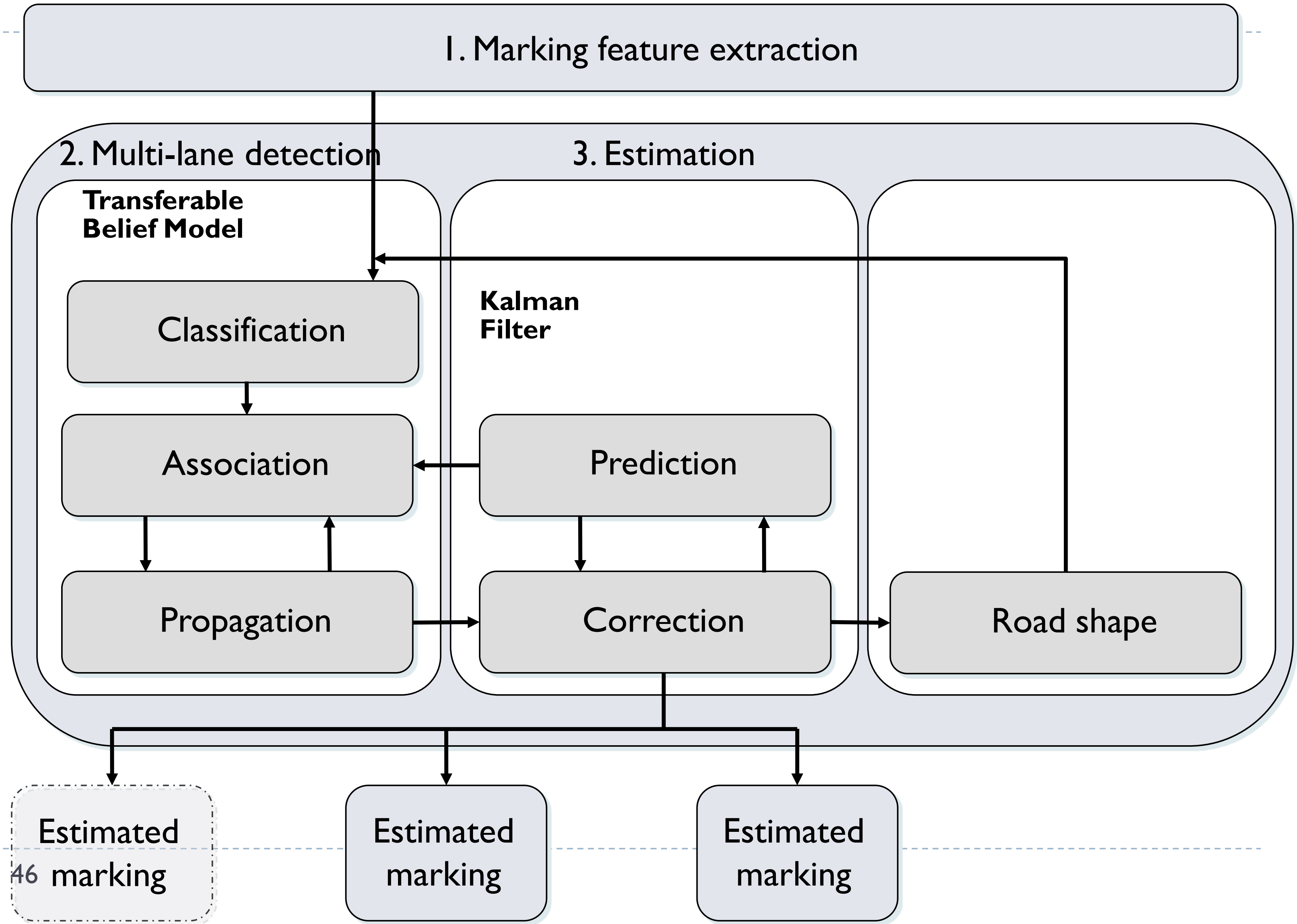


- Number of marking lines N_k
- Shape of marking lines $y = a_0 + a_1 x + a_2 x^2$

Issues

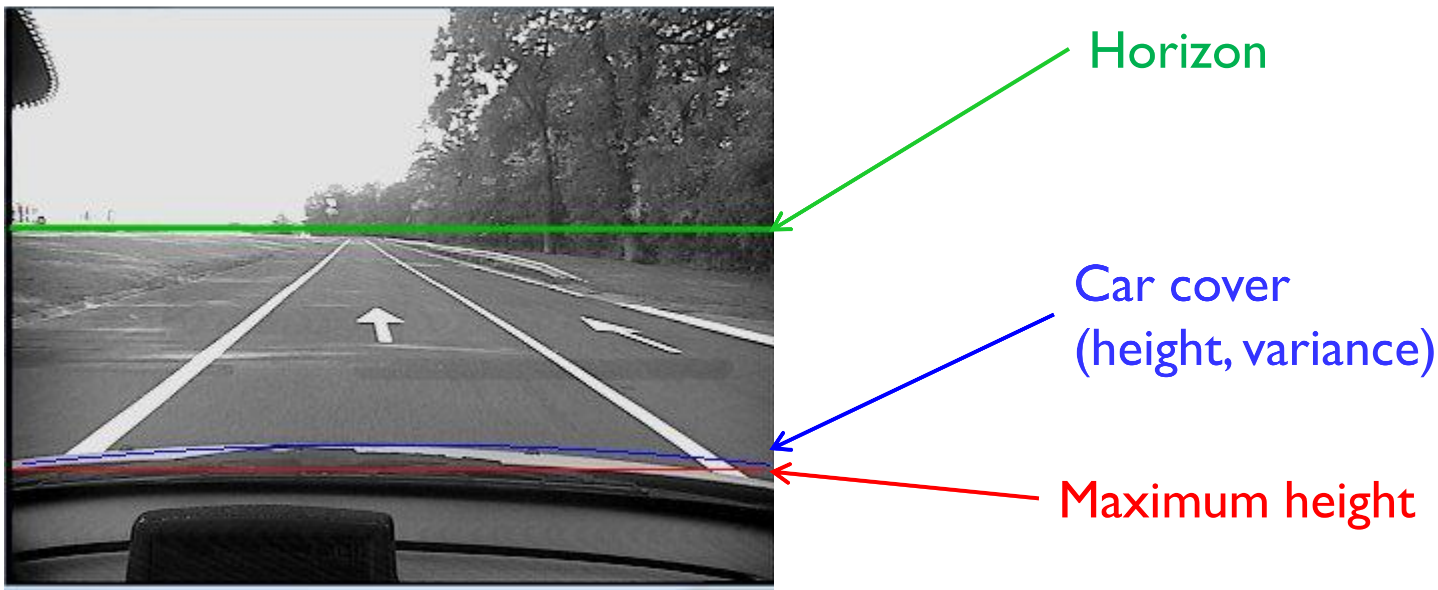
- Missing marking line
- Identification ambiguity
- Curves
- Texture changes
- Line width change
- Shadow
- Light condition change
- False alarm

General scheme



Extraction of road markings primitives

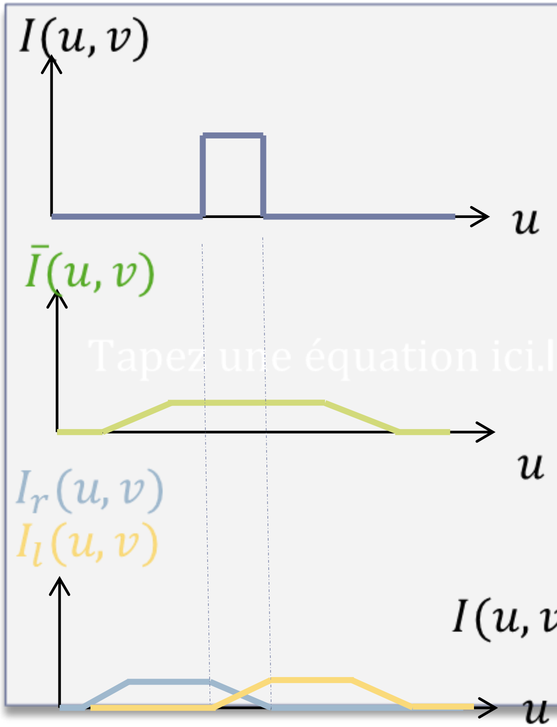
- Computed only in a region of interest to limit false points



[Pollard11a] : Lane Marking Extraction with Combination Strategy and Comparative Evaluation on Synthetic and Camera Images, ITSC, 2011

Local threshold extractor

- LT: Local Threshold
- SLT: Symmetrical Local Threshold

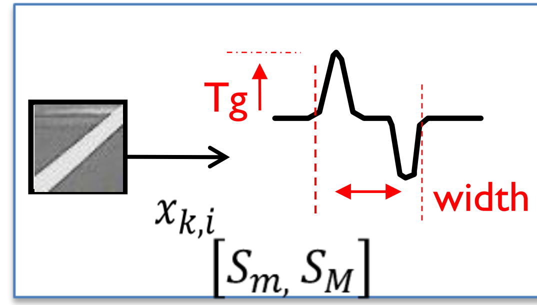


LT

$$I(u,v) > \bar{I} + T_g$$

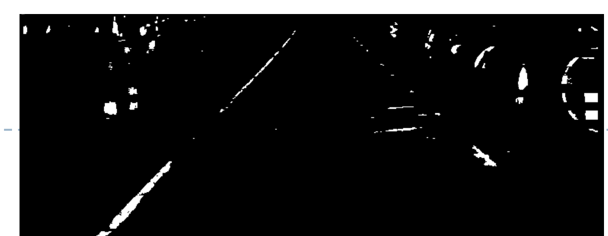
SLT

$$I(u,v) > \max(I_l, I_r) + T_g$$



Drawback

- Depends on the width of the neighborood
- Only horizontal markings
- Sensitive to marks on the road



Background detection extractor

- MLT: Median Local Threshold (50th percentile)
- PLT: Percentil Local threshold (43th percentile)

15	23	21	18	32	43	38	16	19	18	20

{15,16,18,18,19,20,21,23,32,38,43}

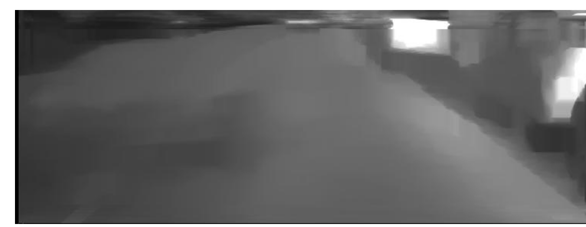
43th percentile value

Median value

I

Horizontal median filter: $\tilde{I}$

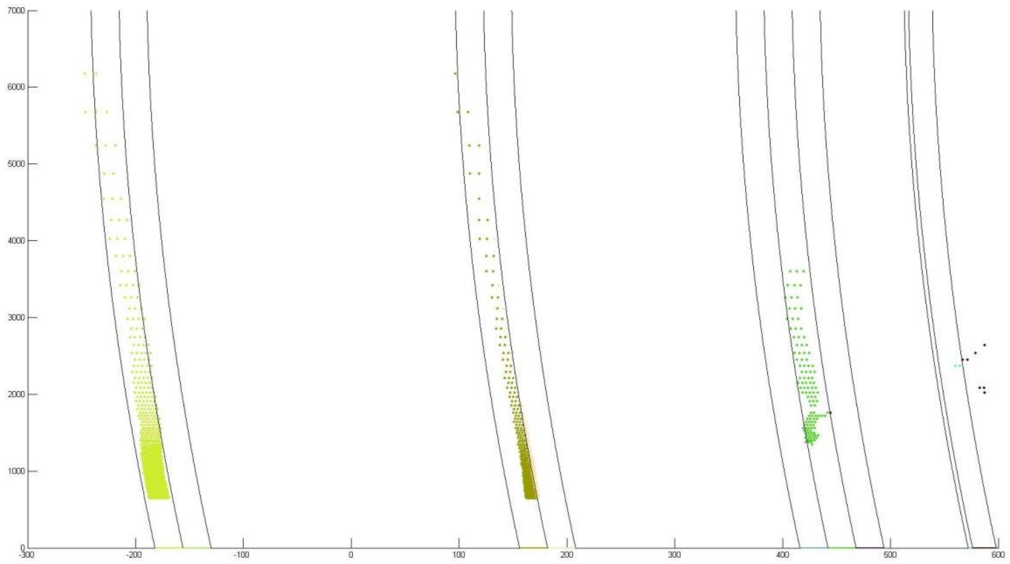
Median filter

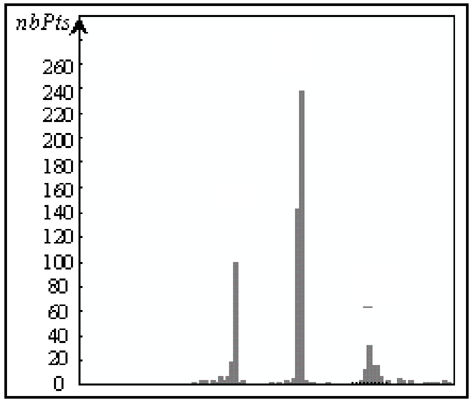


$I - \tilde{I}$

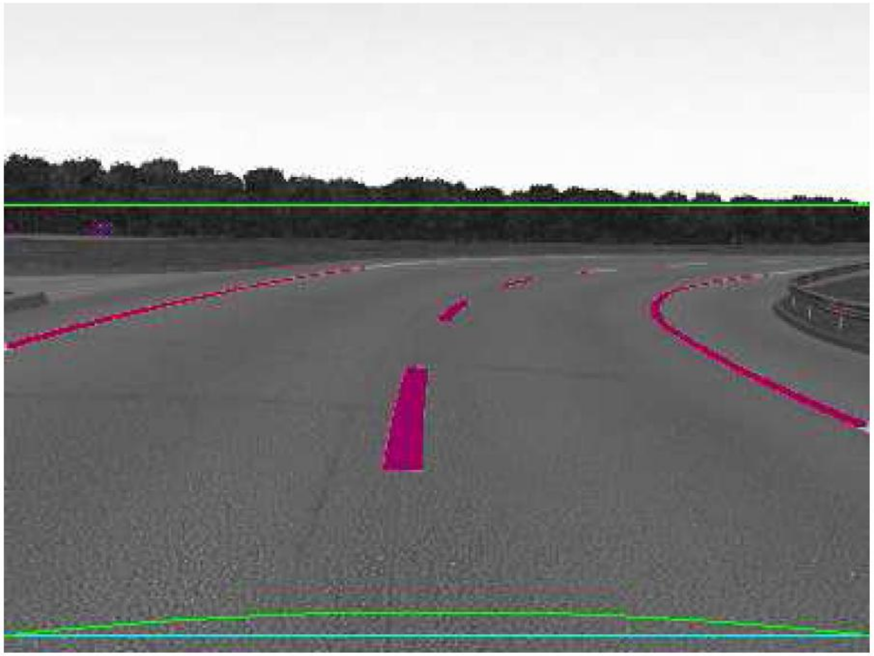
Filtered with $T_g = 100$

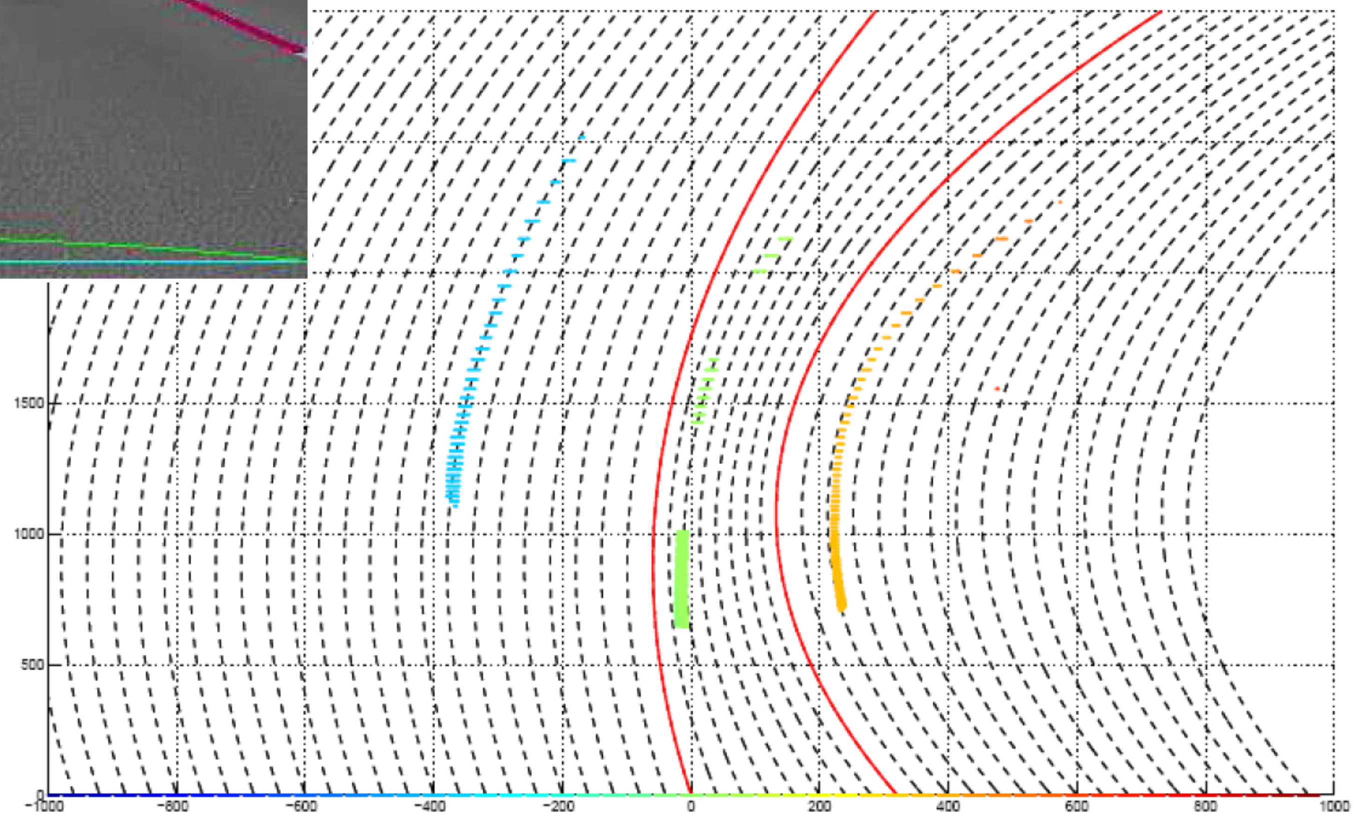
Multi-lane detection





Projection according to the road shape





Multi-lane tracking

- Marking lane

$$y = a_0 + a_1 x + a_2 x^2$$

state vector $A_k = \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix}$

Observations $X_k = \begin{bmatrix} 1 & x_0 & {x_0}^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & {x_n}^2 \end{bmatrix}$ $Y_k = \begin{bmatrix} y_0 \\ \vdots \\ y_n \end{bmatrix}$

state eq. $A_{k+1} = f_k(A_k, v_k)$

v_k: model noise

f_k : transition model

observation eq $Y_k = h(A_k, X_k, w_k)$

h : observation matrix

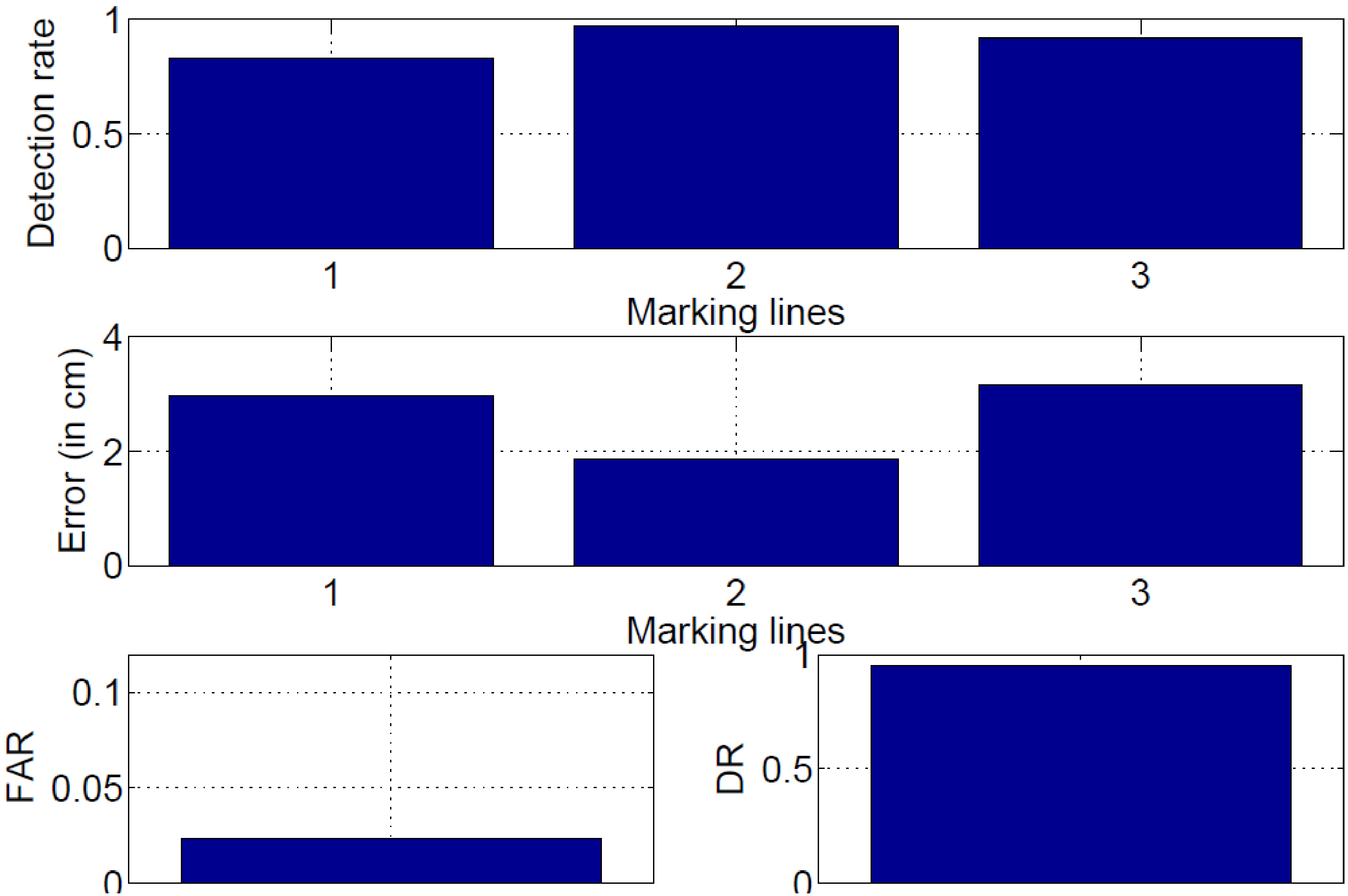
w_k : measurement noise

→ solved by Kalman filter

perspective: use of an IMM for dealing with high curve situation

- [PollardXX]Road Lane Marker Detection and Estimation: a new algorithm and its complete Evaluation Process, submitted to IEEE ITS

Performance evaluation



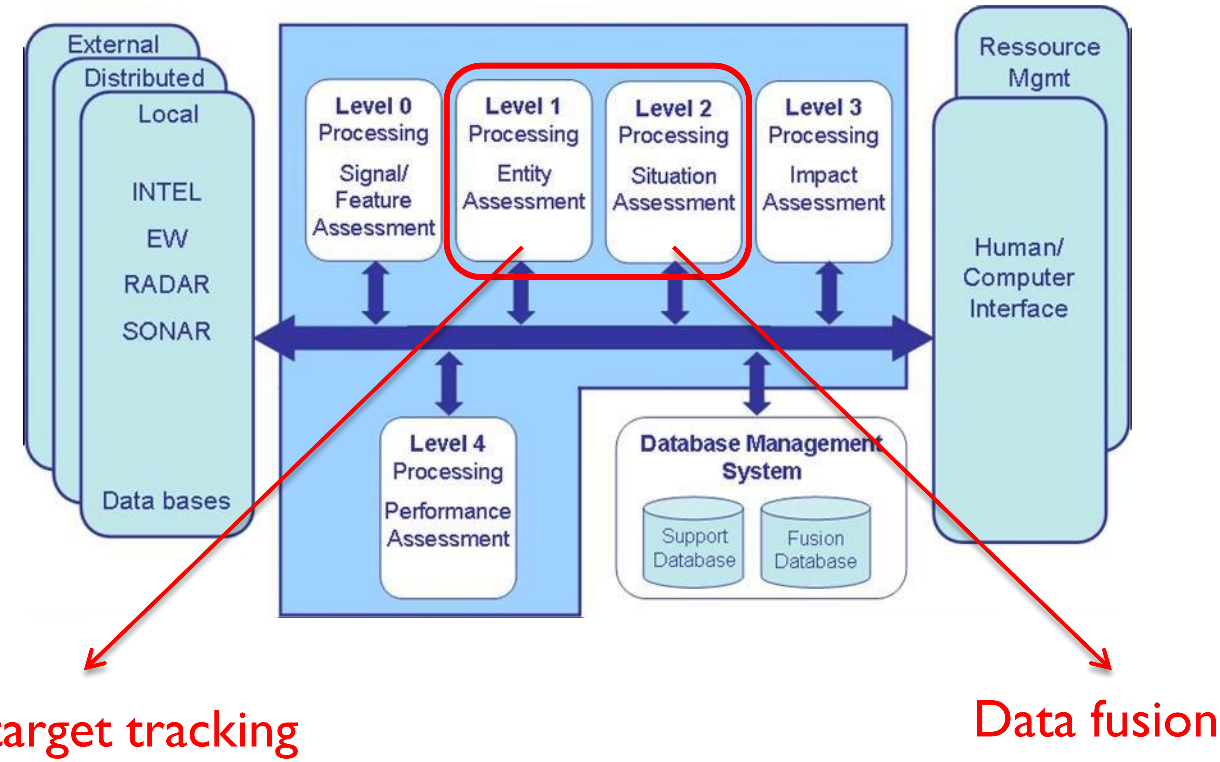
Conclusion

Multitarget Tracking, Situation Assessment,
Object of Interest Detection
Data Fusion, Uncertainty Management,
Evidence Theory, Bayesian Networks
Particle filtering

GMTI, SAR, GPS, GIS, video images

Thank you for your attention!

The Joint Directors of Laboratories



[Steinberg98] : *Revisions to the JDL data fusion model,* Proceedings of SPIE