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# Concurrent Filtering and Smoothing

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# Navigation

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- Tracking position, velocity and orientation of an observer using IMU, GPS, LBL (acoustic), wind speed, camera...

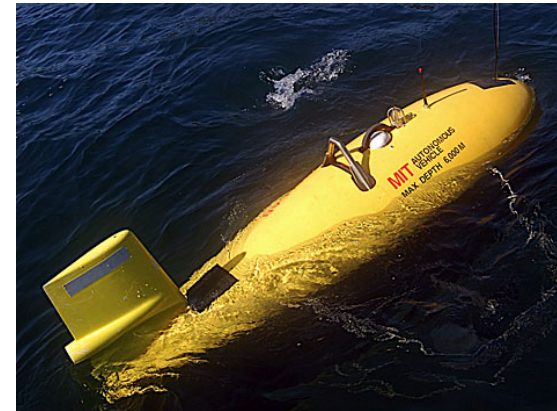
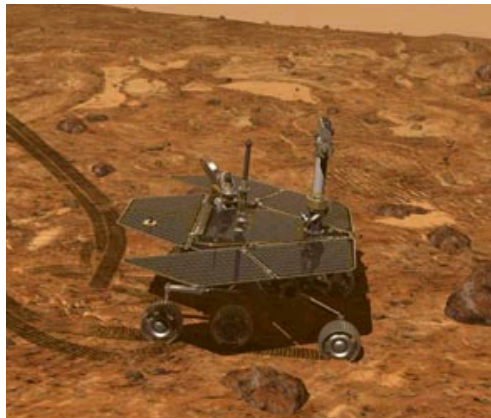


Aircraft

[wikipedia]

Mars Rover

[JPL]



Underwater

[MIT]

- How to solve? Depends on who you ask!

# Navigation Community: Filtering

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- Established, well-tested solution in Aerospace etc.
- Estimate current state
- Objective:

$$\hat{x}_t = \arg \max_{x_t} p(x_t | Z)$$

- Update:

$$p(x_{t+1} | Z) = \int_{x_t} p(x_{t+1}, x_t | Z)$$



[wikipedia]

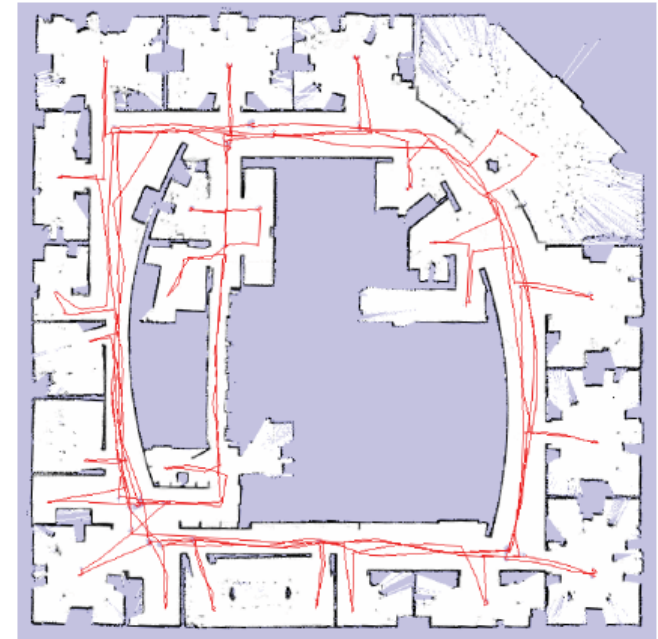
# Robotics Community: Smoothing

- Full SLAM (Simultaneous Localization and Mapping)
- Estimate all states, current and past
- Objective:

$$\hat{X}_t = \arg \max_{X_t} p(X_t | Z)$$

- Update:

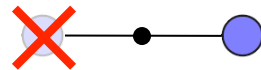
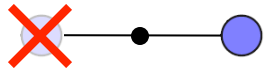
$$p(X_{t+1} | Z) = p(x_{t+1}, X_t | Z)$$



Map of Intel Labs

# Filtering vs. Smoothing

Filtering

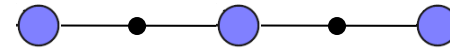


t=0

t=1

t=2

Smoothing



- Constant high frame rate
- Only current state is tracked

- Allows loop closure
- No constant time guarantee

Can we combine the advantages of both methods?

# Filtering and Smoothing

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- Can we combine the advantages of both methods?
- Goals:
  - Perform smoothing in a separate, asynchronous process
  - Maintain real-time performance of the filtering process
    - Minimize calculations of any required synchronization
  - Produce the optimal Bayesian solution

# Related Work

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- **Combining filtering and loop closing** [Eustice, Singh, and Leonard 2006]
  - Uses an augmented state filter to allow loop closures
  - Maintains real-time performance
  - Produces only an approximate solution
- **Parallel tracking and mapping** [Klein and Murray 2007] [Newcombe et al. 2011]
  - Performs Bundle Adjustment (BA) in a separate process
  - Relocalizes after BA instead of fusing results
  - Does not incorporate additional navigation sensors
- **Dual-layer estimator** [Mourikis and Roumeliotis 2008]
  - Combines an EKF with BA
  - EKF must be rolled back to incorporate the BA update in a consistent manner

# Filtering and Smoothing (Cont.)

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- In this work:
  - We perform smoothing and filtering in parallel
    - High-rate measurements are processed by the filter
    - Loop closures are added directly to the smoother
  - Smoothing and filtering are considered two components of a single optimization problem
    - Ensures the optimal Bayesian estimate is obtained
  - The problem is represented using a Bayes tree
    - Intuitive graphical model
    - Exploits sparsity
    - Allows incremental inference



# Bayes Tree

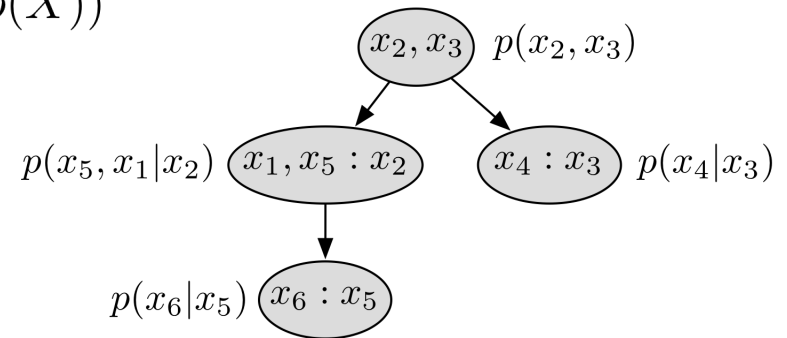
- The maximum a posteriori (MAP) estimate is given by

$$\hat{X} = \arg \max_X (p(X))$$

- Applying the chain rule yields a factorization:

$$p(X) = \prod_i p(X_i | S_i)$$

- where  $X_i, S_i \subset X$



- Different factorizations exist, **depending on the order in which variables are chosen**
- Given a particular factorization, a unique Bayes tree can be constructed
  - Each node represents a conditional distribution
  - Each node is conditioned only on its ancestors in the tree
  - Solving for  $\hat{X}$  involves applying the chain rule, starting from the root

# Bayes Tree

- The maximum a posteriori (MAP) estimate is given by

$$\hat{X} = \arg \max (p(X))$$

- Applying the

– when

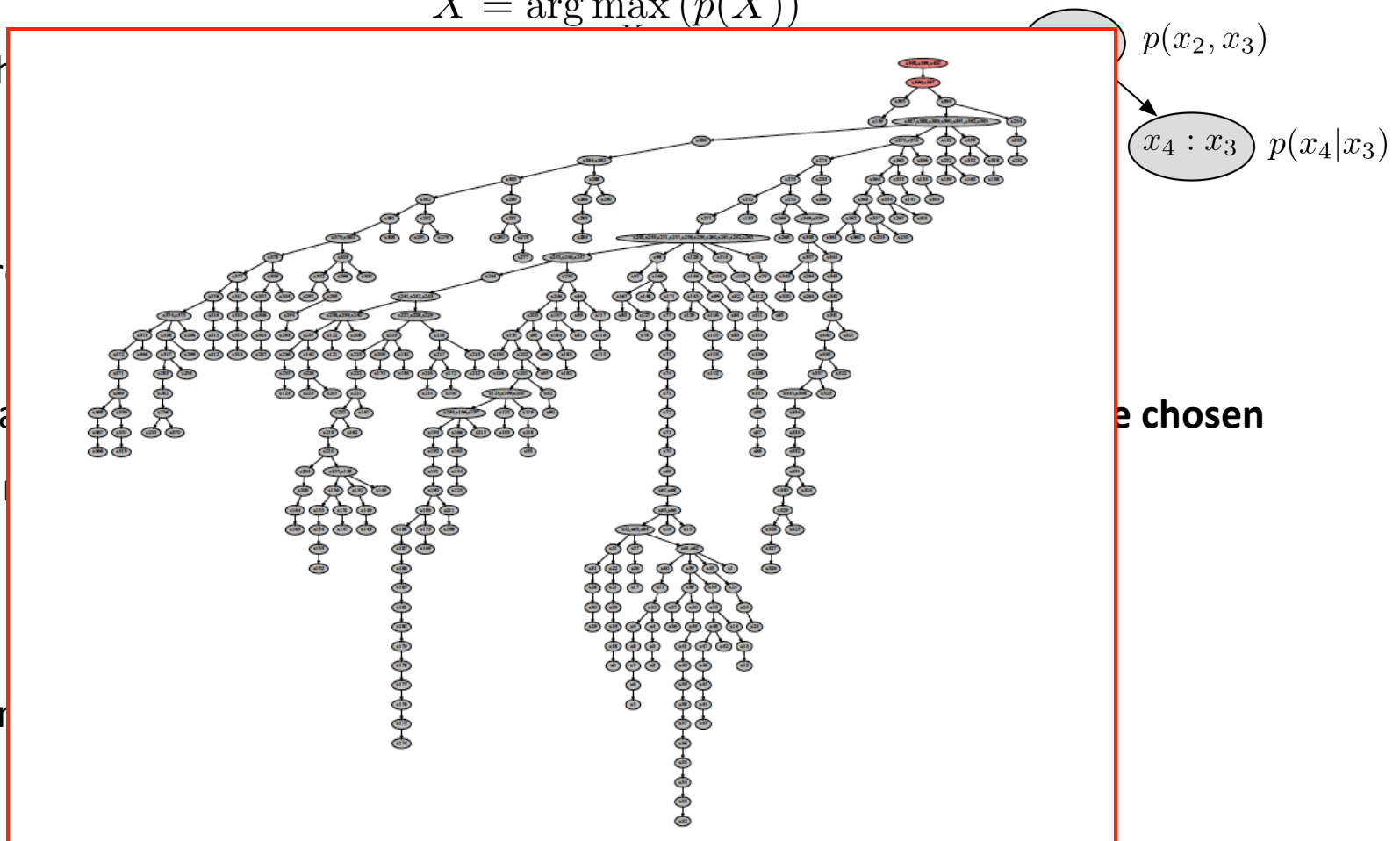
- Different factors

- Given a pair

– Each

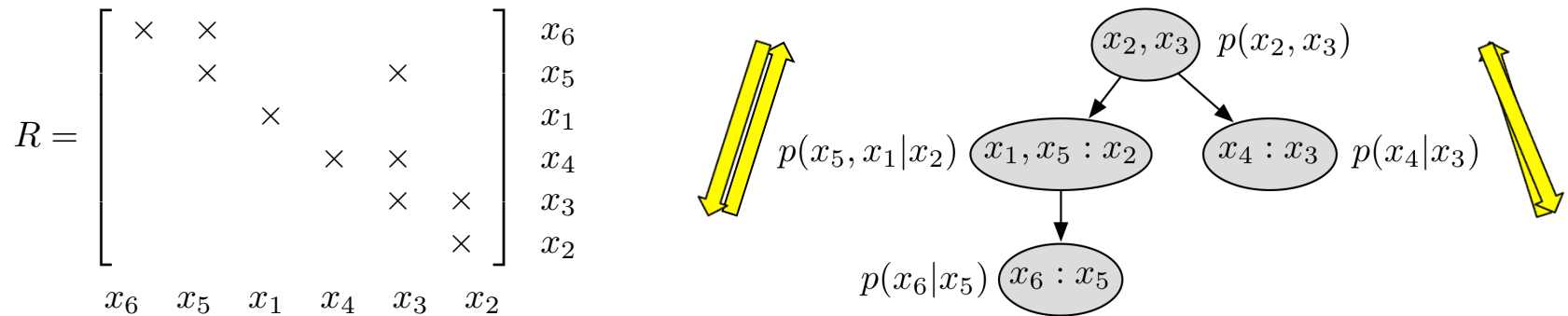
– Each

– Solving



# Bayes Tree – Gaussian Distribution

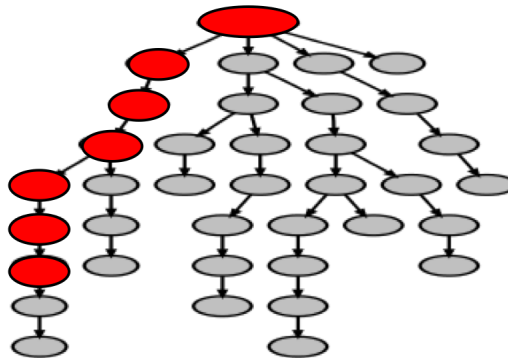
- Bayes tree corresponds to the square root information matrix  $\mathcal{I} = R^T R$



- **Factorization\Elimination** (i.e. calculation of R) corresponds to constructing the Bayes tree
  - Performed from bottom upwards
- Solving for  $\hat{X}$ :
  - Performed by **back-substitution**, from root of Bayes tree downwards

# Efficient Bayes Tree Updates [Kaess et al IJRR 12]

- Key Insights
  - **Incorporating new measurements can be done efficiently**
  - Affects only variables involved in the measurement model and their ancestors
    - Only affects variables in the path to the top of the tree
    - Branches remain unaffected



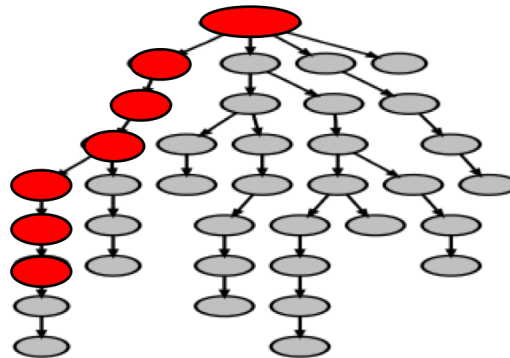
# Efficient Bayes Tree Updates [Kaess et al IJRR 12]

- Key Insights

- Many variable orderings exist

- Ordering affects:

- Tree structure - different factorization of  $p(X) = \prod_i p(X_i|S_i)$
    - Number of variables in each node / Computational complexity
    - Does not affect the solution

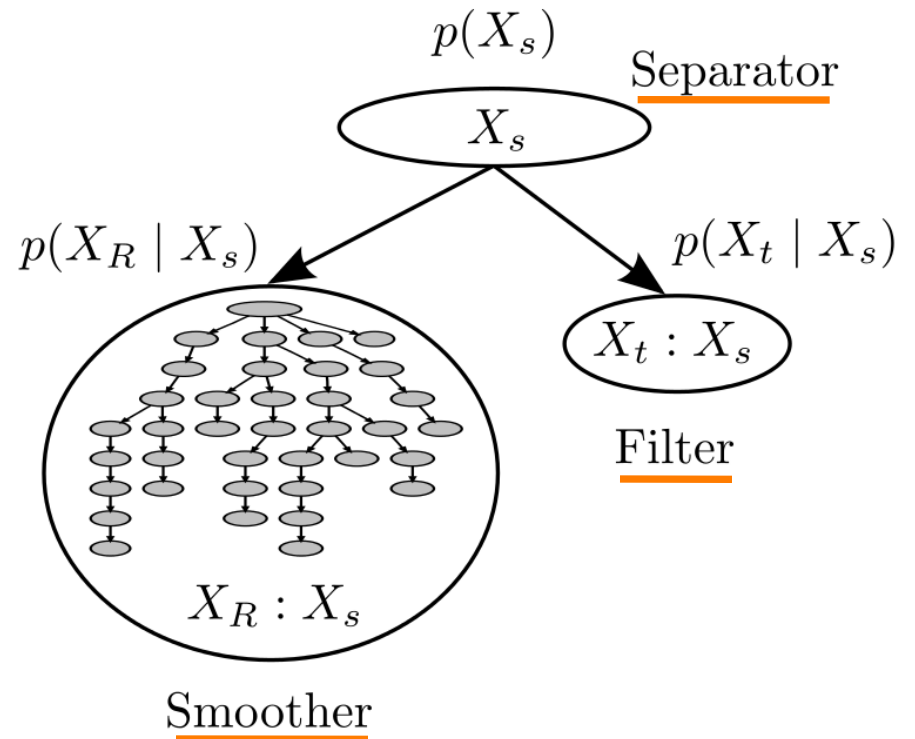


# Parallelizing Filtering and Smoothing

- Factorization based on suitable variable ordering:

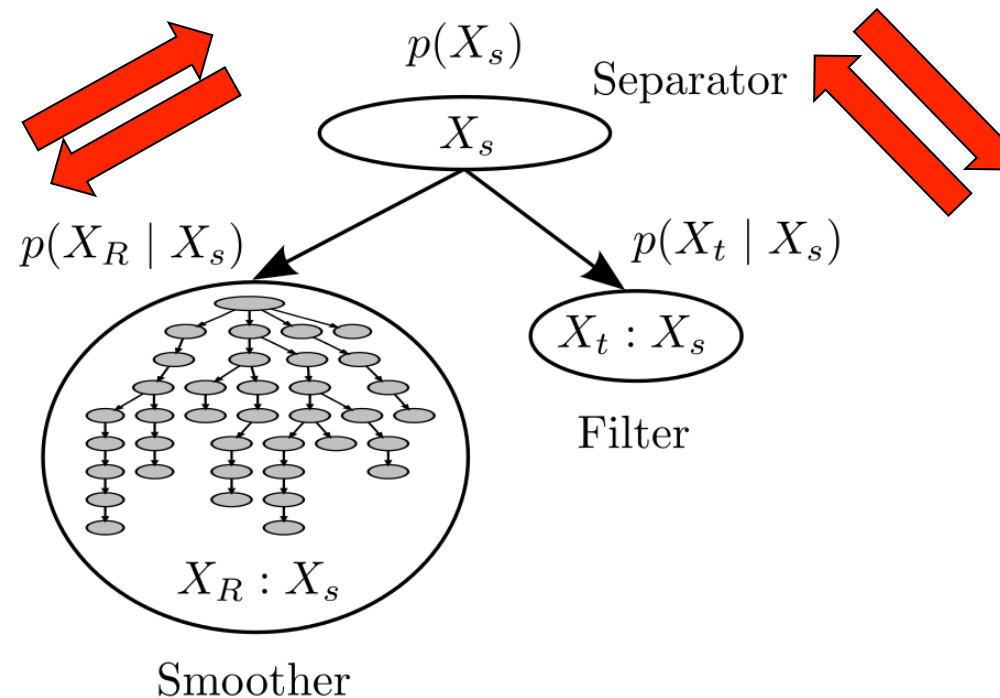
$$p(X) = p(X_R | X_s) p(X_s) p(X_t | X_s)$$

- Corresponding Bayes tree:
- Allows concurrent updates to filter and smoother!



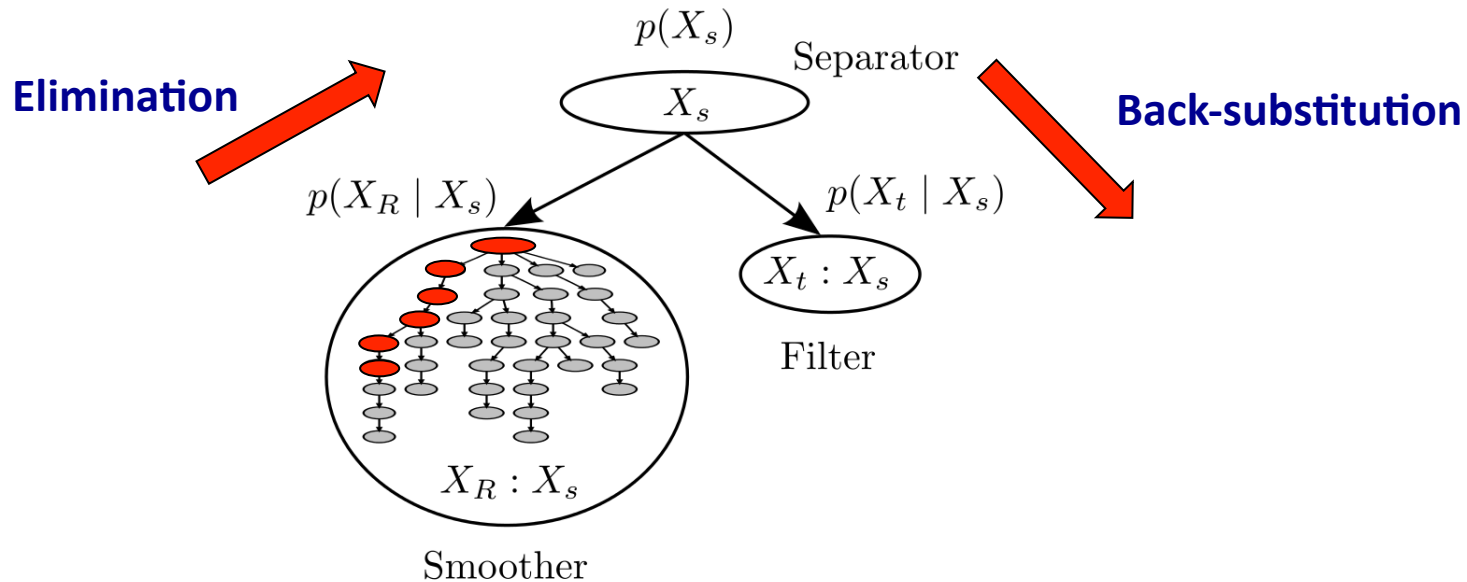
# Parallelizing Filtering and Smoothing

- Filter and smoother are kept periodically synchronized
  - Information flows between the smoother and the filter via the separator



# Parallelizing Filtering and Smoothing

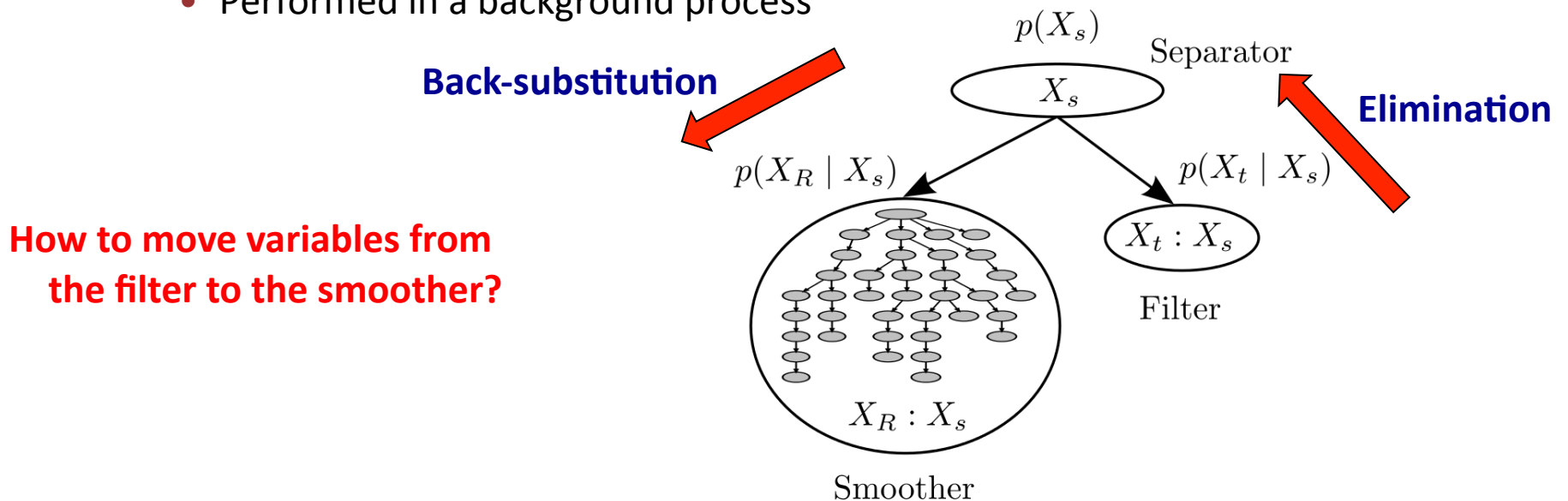
- Loop closure measurements are added to the smoother
  - Smoother processes new measurements in a background process
  - Upon completion, the separator (root of the Bayes tree) is updated
  - Updates from the root are propagated to the filter in a fast process
    - Involves only a small number of variables





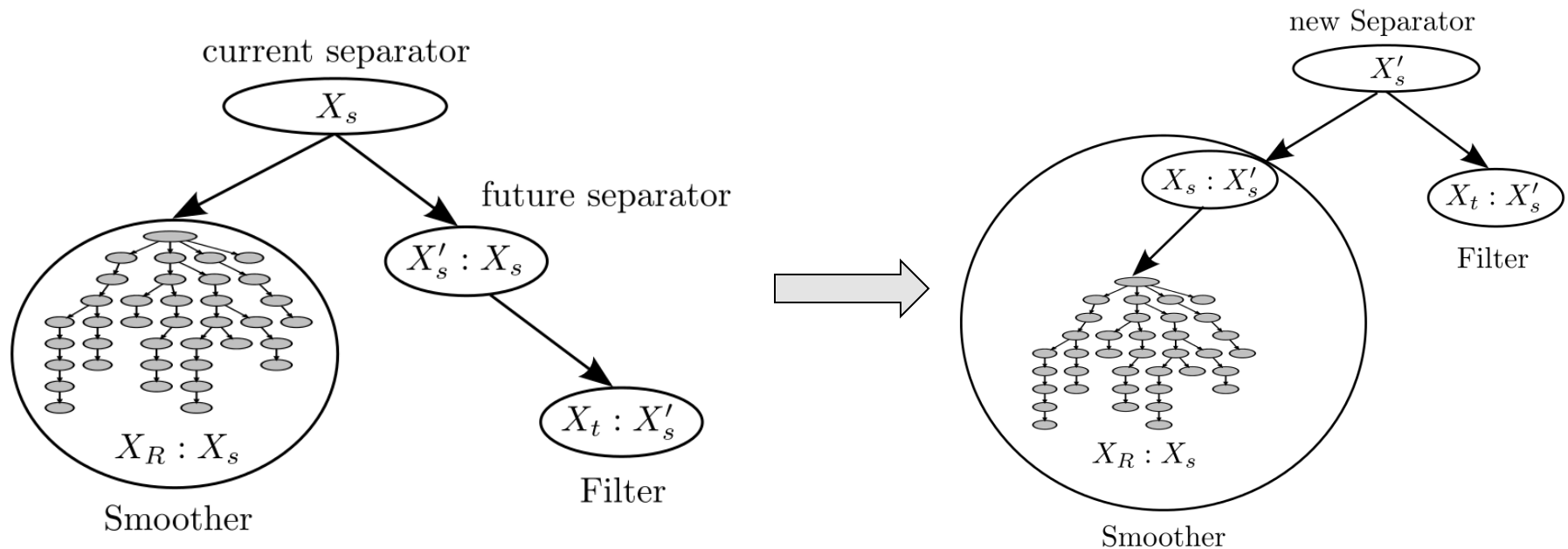
# Parallelizing Filtering and Smoothing

- **High-rate measurements are added to the filter**
  - Filter processes measurements in real time
    - Separator (root) is updated as part of this process
  - The separator accumulates updates
  - When the smoother is available:
    - Propagate these updates to the smoother
    - Performed in a background process



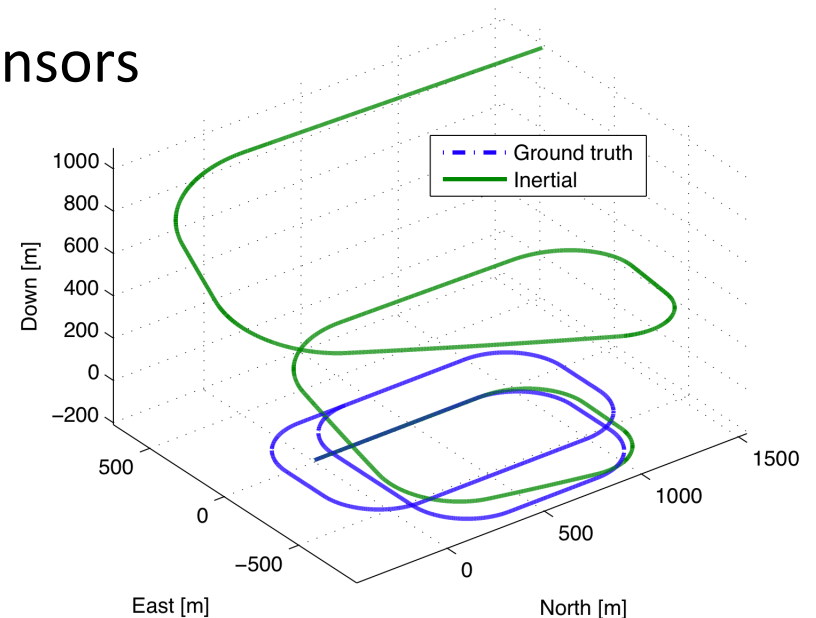
# Moving Variables to the Smoother

- As time progresses, the filter maintains a sparse set of variables
- These variables form a chain of nodes on the filter side of the Bayes tree
- Whenever the smoother is available:
  - The current separator (root) node is moved to the smoother
  - A new separator is formed from the chain on the filter side
  - This is achieved by choosing a new variable ordering for these two nodes



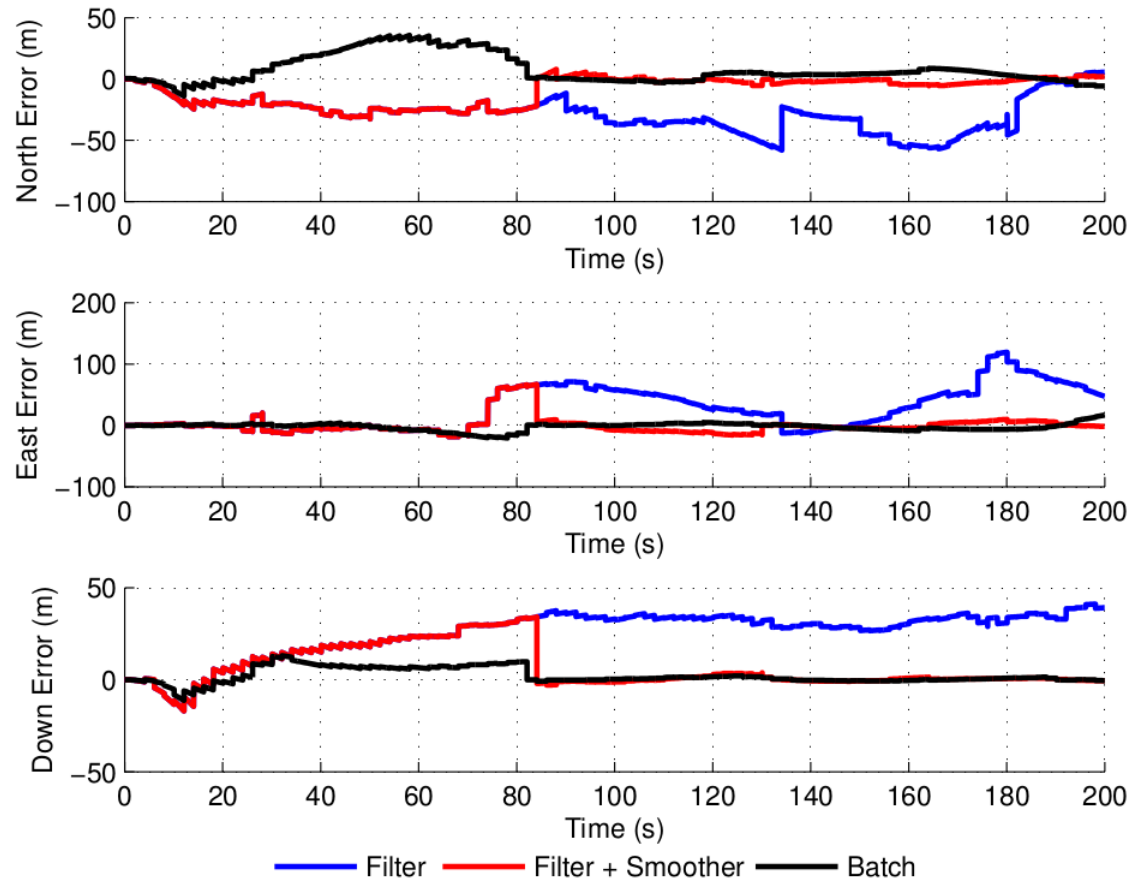
# Evaluation: Simulation

- Simulated flight of an aerial vehicle
  - Velocity: 40 m/s
  - Constant height: 200 m above mean ground level
  - Ground elevation:  $\pm 50$  m
- Synthetic measurements of different sensors
  - IMU at 100 Hz
  - Stereo camera at 0.5Hz
    - Produces **relative pose** measurements
  - Sparse loop closures found in camera data
    - 22 loop closure events identified
    - Provided directly to the smoother



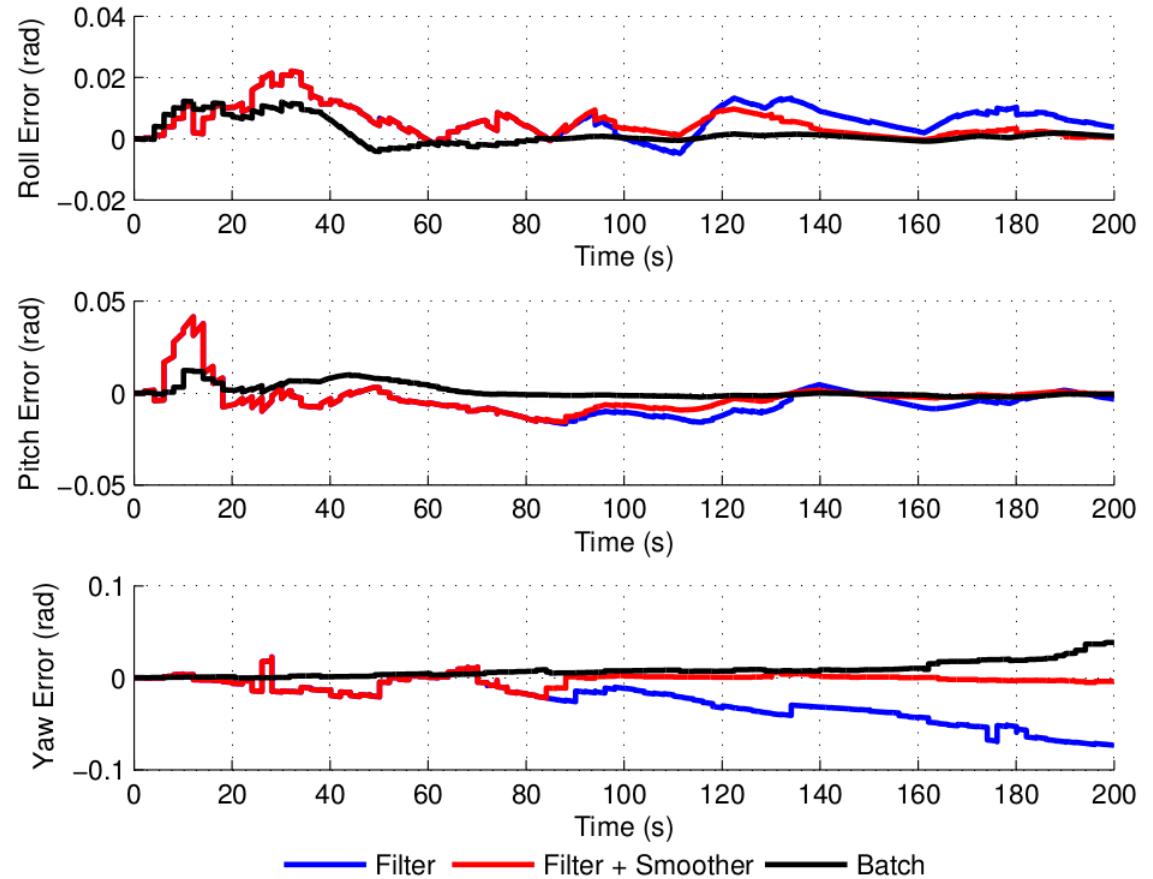
# Evaluation: Positional Error

- Compared methods:
  - **Filter alone**
  - **Concurrent Filter and Smoother**  
(Our approach)
  - **Incremental Batch**



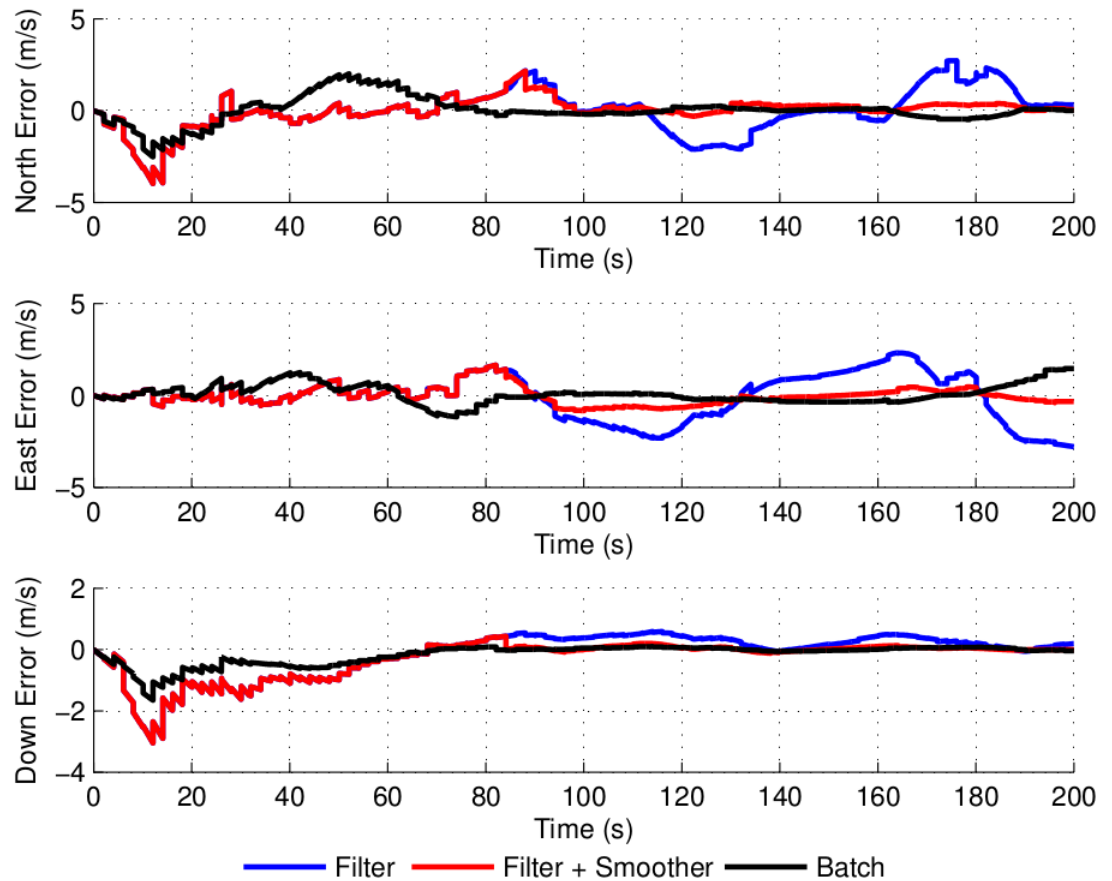
# Evaluation: Rotational Error

- Compared methods:
  - **Filter alone**
  - **Concurrent Filter and Smoother**  
(Our approach)
  - **Incremental Batch**



# Evaluation: Velocity Error

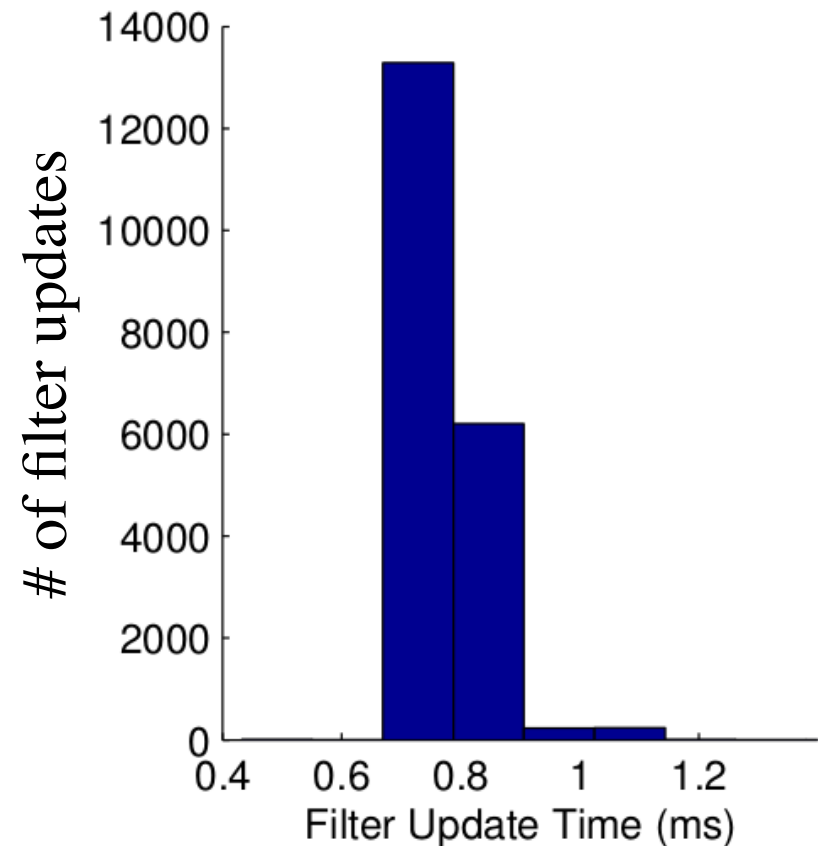
- Compared methods:
  - **Filter alone**
  - **Concurrent Filter and Smoother**  
(Our approach)
  - **Incremental Batch**



# Timing: Filter Update

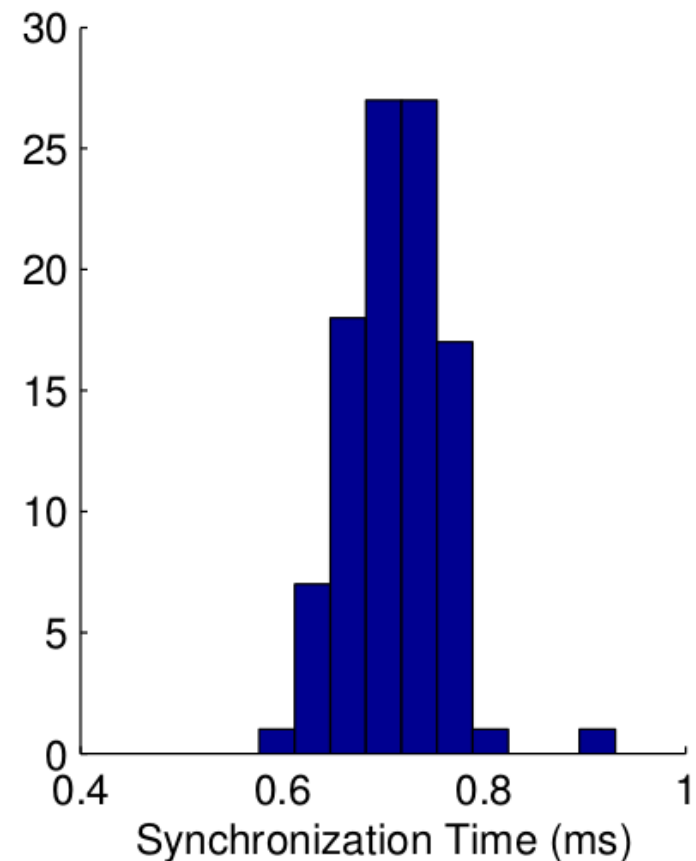
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- Filter updates in constant time
- Confirmed by evaluation:



# Timing: Synchronization

- Synchronization only affects top of tree
  - Performed after smoother is done
- Depends on size of root clique
- Evaluation shows very fast synchronization





# Future Work

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- Relinearization
  - Filter produces linear conditionals
  - “Lifting” of linear constraints (Konolige, TRO 2008)
- Bound complexity of smoother
  - Fixed-lag
  - Sparsification (SLAM)

# Summary

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- We combined filtering and smoothing
  - Parallel formulation in Bayes tree
  - Constant time filtering
  - Loop closing capability
  
- Tomorrow:
  - “Factor Graph Based Incremental Smoothing in Inertial Navigation Systems”  
V. Indelman, S. Williams, M. Kaess, F. Dellaert