Applications

- ✓ Signal processing
  - Short signal classification for speech labelling `(Deller)`
  - Adaptive blind equalization for multichannel systems `(Huang)`
  - Estimation of time-varying magnitude harmonics `(Yaz)`
  - Audio frequency filter identification
- ✓ Information theory
  - Symbol-by-symbol decoding for binary data transmission `(Wells)`
  - Model reduction for channel models
- ✓ Fault detection
  - Fault detection and isolation in chemical MIMO plants
  - Non destructive testing of material structures

- ✓ Image processing and computer vision
  - Tomographic feature detection and classification (Hero III)
  - Image reconstruction with mixed stochastic/bounded error (Chaumette)
  - Recursive time-to-collision estimation (Vicino)
- ✓ Semiconductor manufacturing
  - Nonlinear filtering (Khargonekar, Tsakalis)
- ✓ Ecology
  - Prediction of lake eutrophication (Keesman)
  - Greenhouse energy requirement prediction (Maksarov)
  - Long-term stability of shallow lakes
- ✓ Mobile robotics and autonomous navigation
  - Real-time robot localization (Sabater, Hanebeck, Vicino,...)
  - Obstacle modeling (Ruiz, Meizel)
  - Robust observers for robot tracking (Walter, Meizel)
  - Simultaneous localization and mapping (Vicino)

Simultaneous Localization and Mapping (SLAM)

⇛ A fundamental problem in autonomous navigation and mobile robotics

Two tasks: *self localization* and *map building*

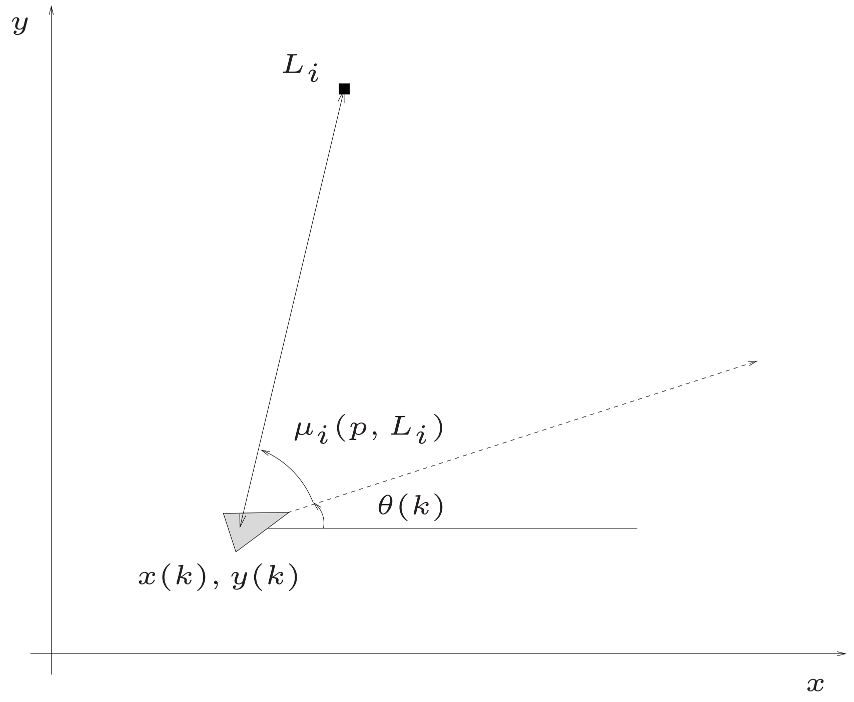
Problem setting

✓ a *landmark-based* map of the environment $L_i = (x_{L_i}, y_{L_i})$

✓ an *uncertain dynamic model* of the vehicle pose $p(k) = [x(k)\ y(k)\ \theta(k)]'$

✓ *exteroceptive measurements* with respect to the landmarks:

- distance measurements
- relative angular measurements



Formulation of SLAM problem

Landmark location *and* robot pose must be estimated simultaneously!
State vector: $X(k) = [p'(k) \;\; L_1'(k) \;\; \cdots \;\; L_n'(k)]'$

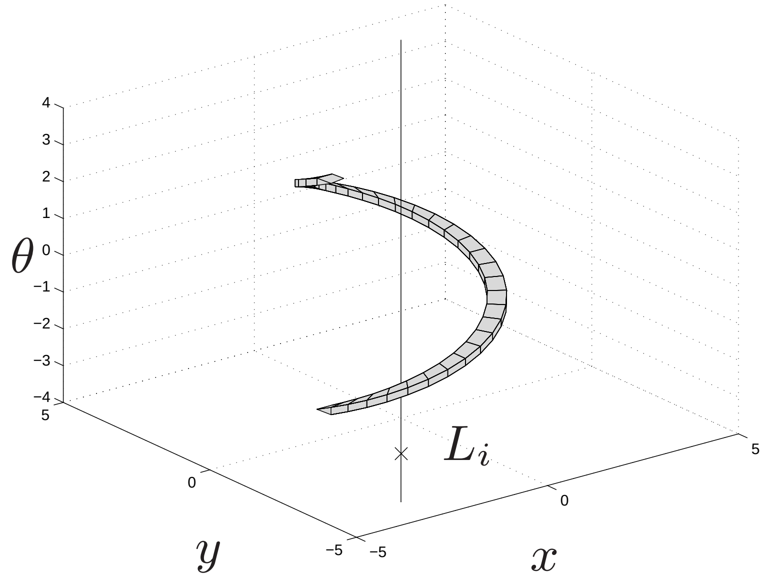
State estimation problem usually tackled in statistical framework
(EKF, Markov estimation, iconic matching...)

Assumption: UBB unmodeled dynamics and measurement errors
$\rightarrow$ SLAM problem can be formulated in the set membership setting

SM SLAM Problem: Let $\Xi(0) \subset \mathbb{R}^{2n+3}$ be a set containing the initial pose of the vehicle and the position of the landmarks, $X(0)$. Given the dynamic model and measurement equations, find at each time $k = 1, 2, \cdots$, the set $\Xi(k|k)$ of state vectors $X(k)$ compatible with model, measurements and UBB noise assumptions.

Main problem: nonlinear measurements equations lead to nonlinear and nonconvex feasible sets

→ efficient approximations required (accurate and fast)



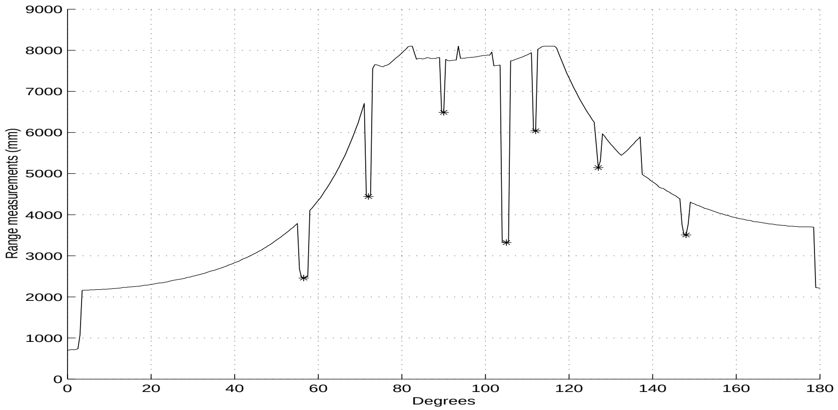
set of feasible poses for a pair of measures (distance and orientation) w.r.t. L_i

Towards efficient SM SLAM algorithms

- ✓ state decomposition into subsets of state variables (robot pose, landmark positions)
- ✓ guaranteed set membership estimation of each subset
- ✓ set approximations via simple regions (boxes, parallelotopes)
- ✓ low computational complexity ⇒ suitable for real-time applications

Experimental testing: setup

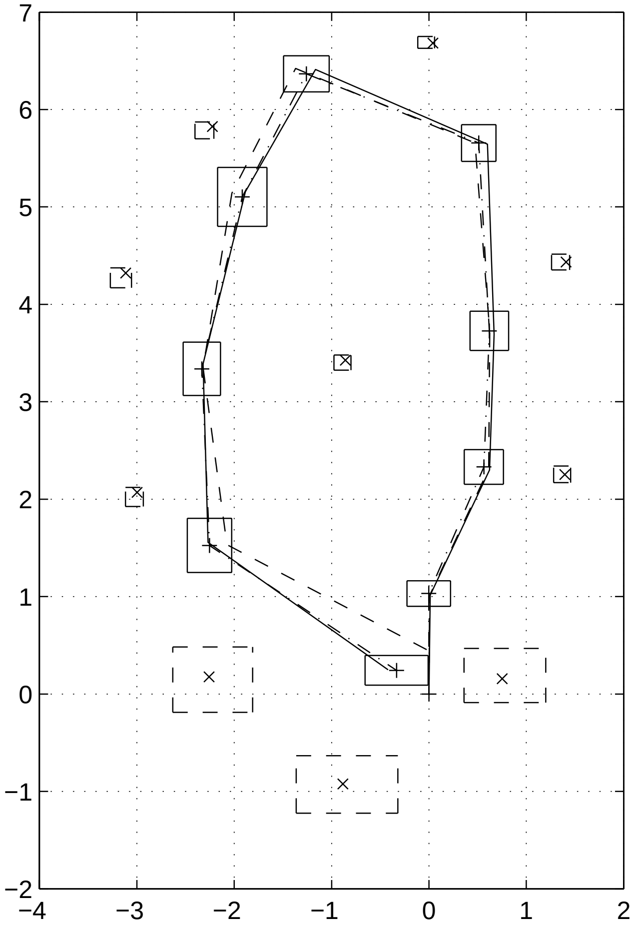
- ◊ mobile robot Nomad XR4000
- ◊ 10 artificial landmarks
- ◊ angular and distance measures from laser rangefinder
- ◊ measurement error bounds from landmark extraction



planar laser rangefinder:

180° scanning angle and 0.5° resolution

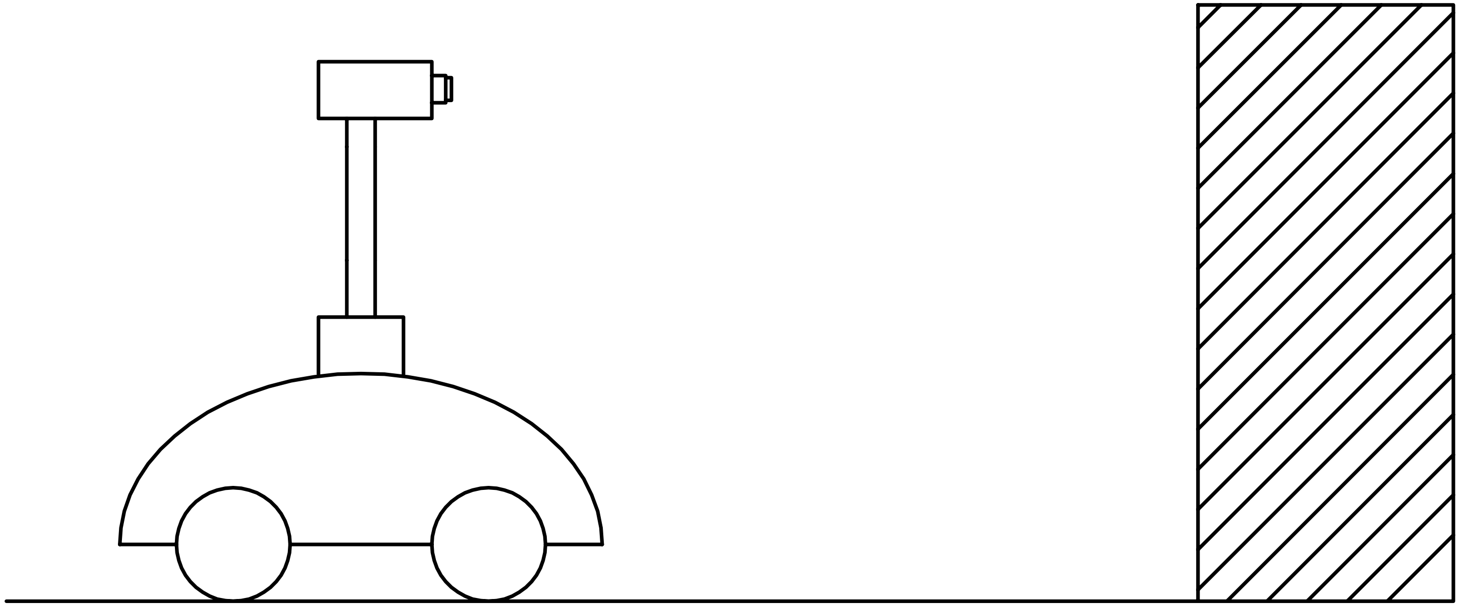
Experimental testing: results



nominal trajectory (odometry): dashed
true trajectory: solid
estimated trajectory: dash-dotted

- ▷ average robot position and heading errors: 4 cm, 0.67°
- ▷ average robot position and orientation uncertainty: 0.17 m^2, 10.3°
- ▷ average landmark position error: 3 cm
- ▷ average landmark uncertainty region: 0.18 m^2
- ▷ average number of landmarks detected at each measurement step: ~ 6
- ▷ time required at each measurement step: ~ 0.1 sec.

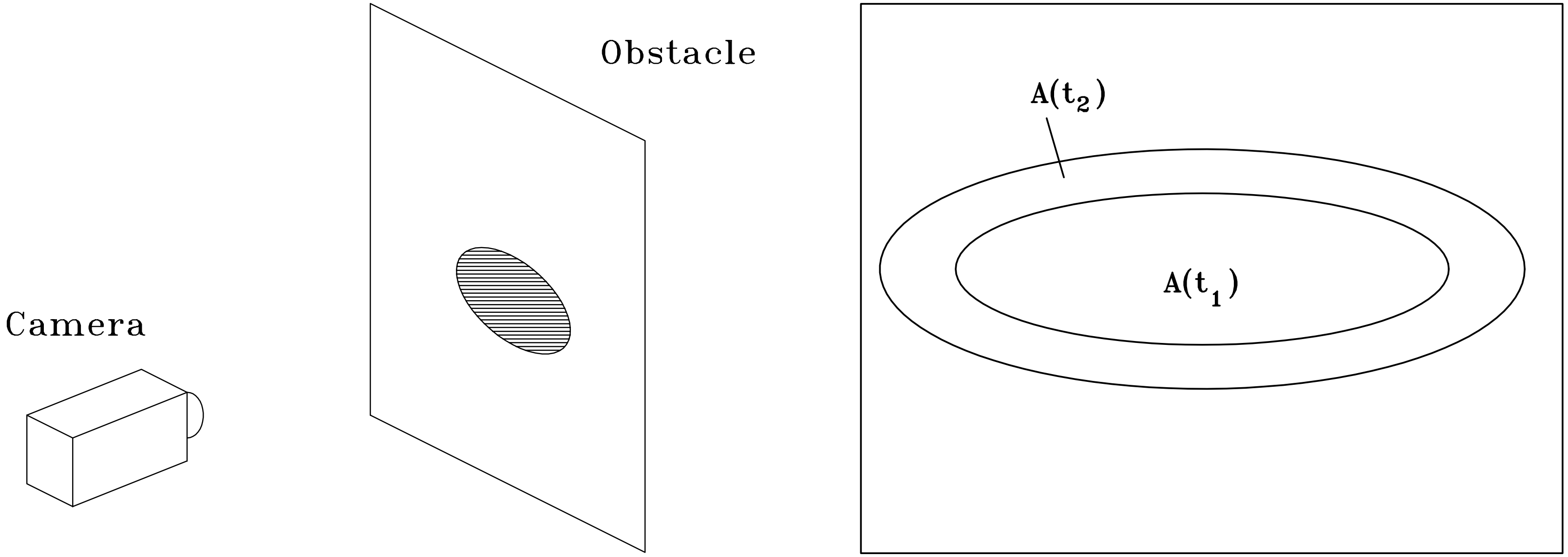
Time-to-contact estimation



$$\tau(t) = \text{time-to-contact} = \frac{L(t)}{V}$$

Time remaining before the observing sensor and the object come to collision, under the hypothesis of uniform relative motion

Differential invariants approach

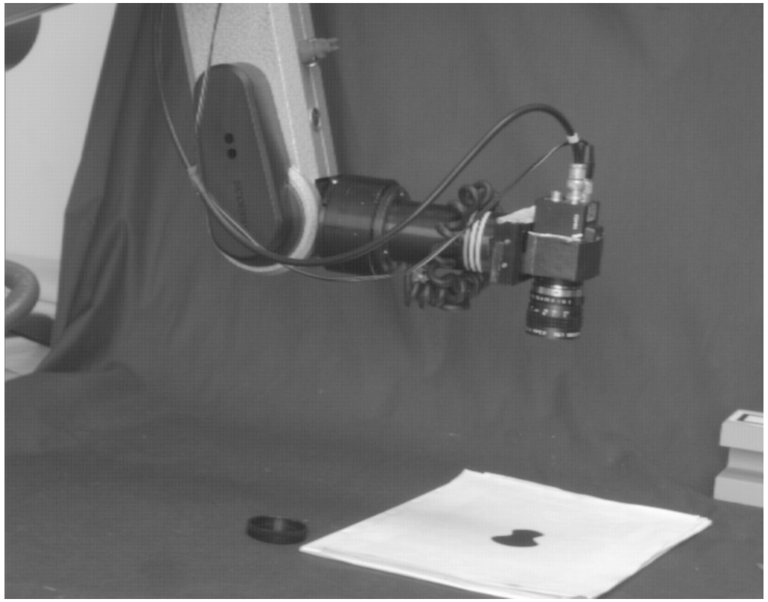


$A(t)$: area enclosed by the object contour at time t

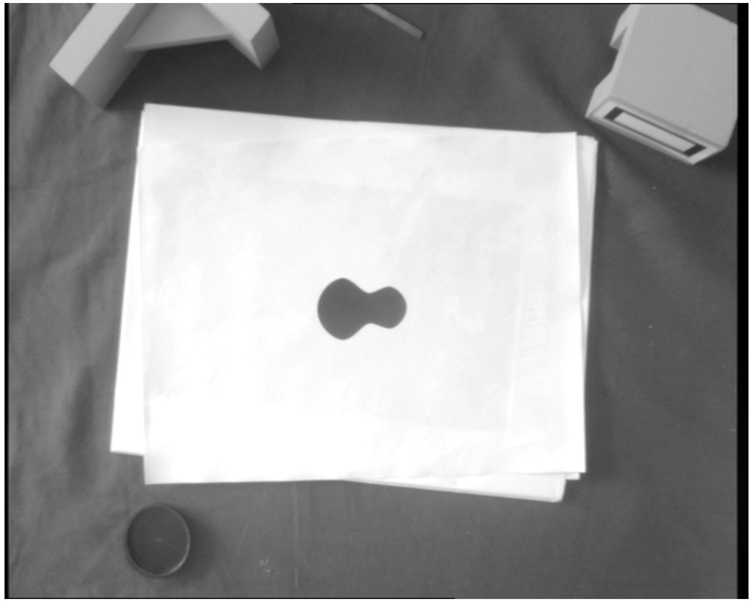
Main result [Cipolla 1997]

$$\tau(t) = \frac{2A(t)}{\dot{A}(t)}$$

Time-to-contact estimation: experimental results



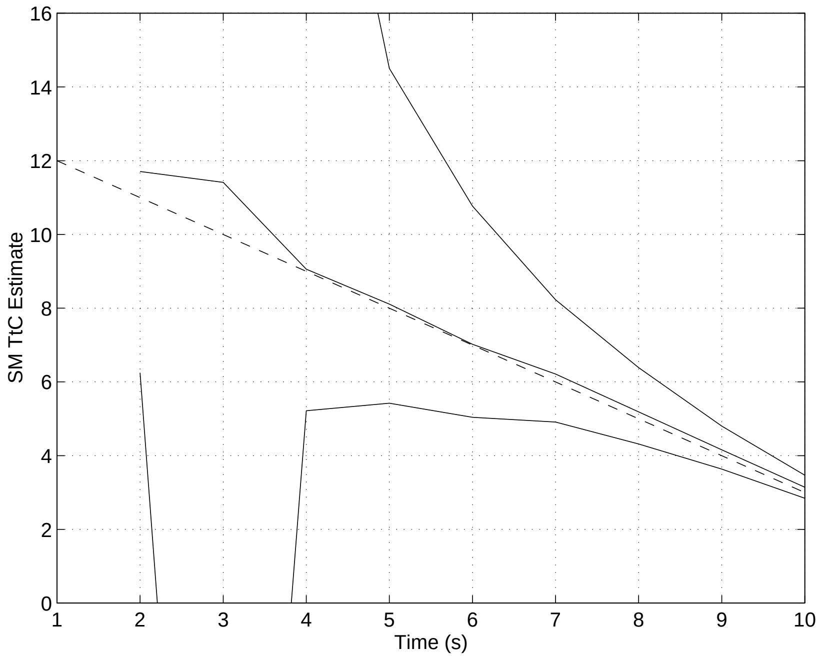
Experimental setup



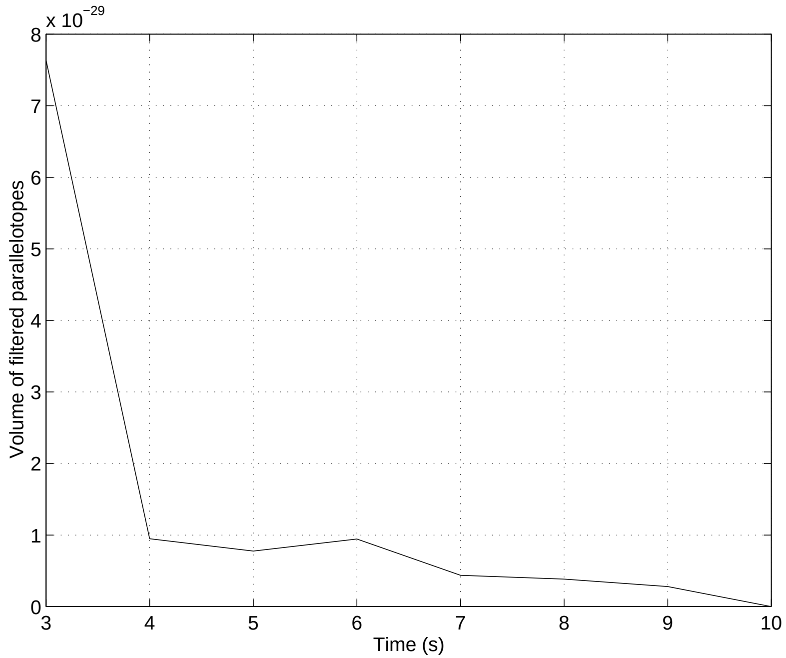
First image

10 images – sample time: 1 sec.

Experimental results



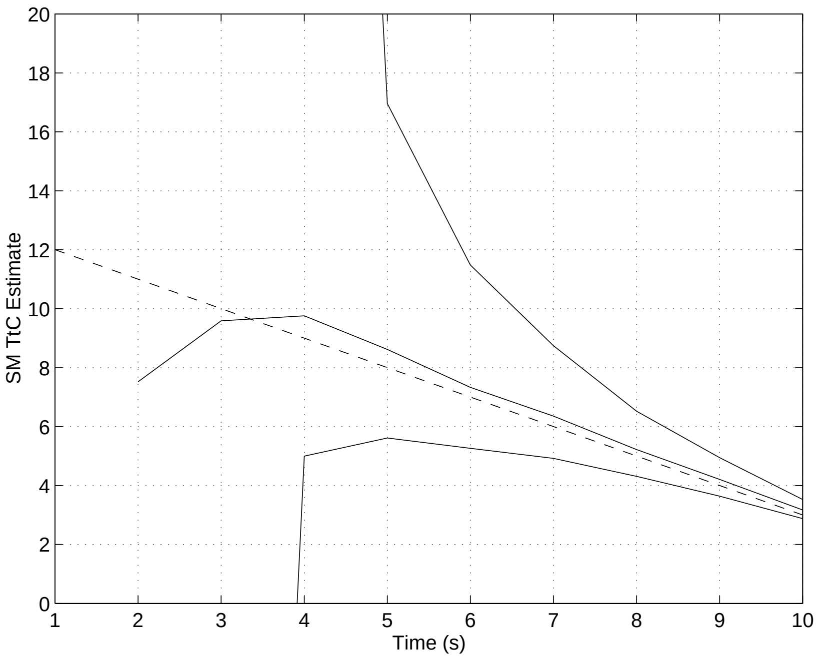
Ttc estimates and error bounds (ideal motion model)



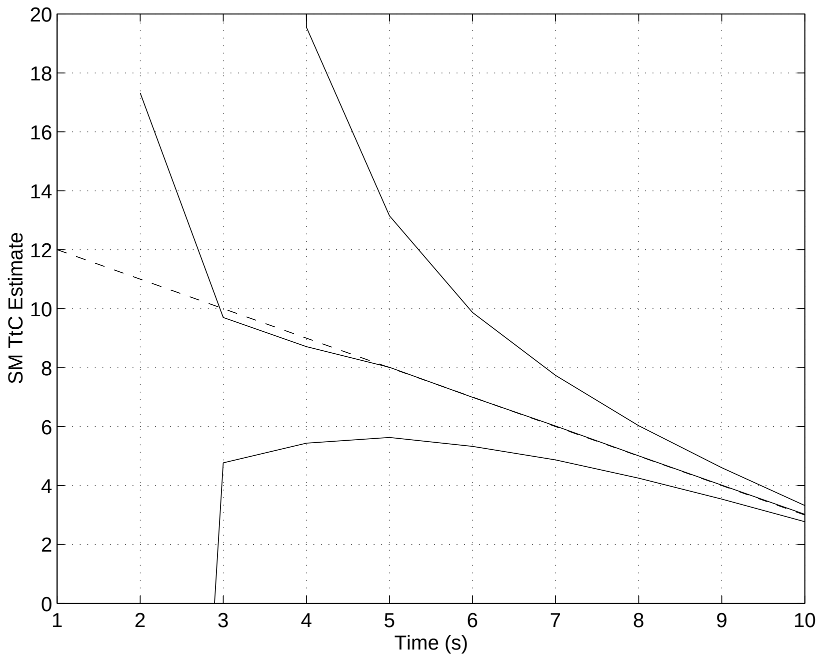
Membership sets volumes

Adaptive strategies

Main idea: exploit the current time-to-contact estimate to update the system dynamic model

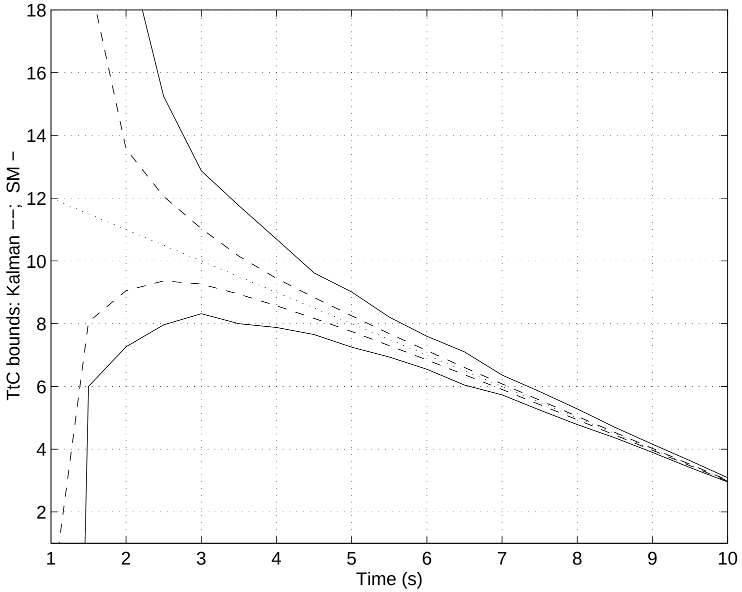


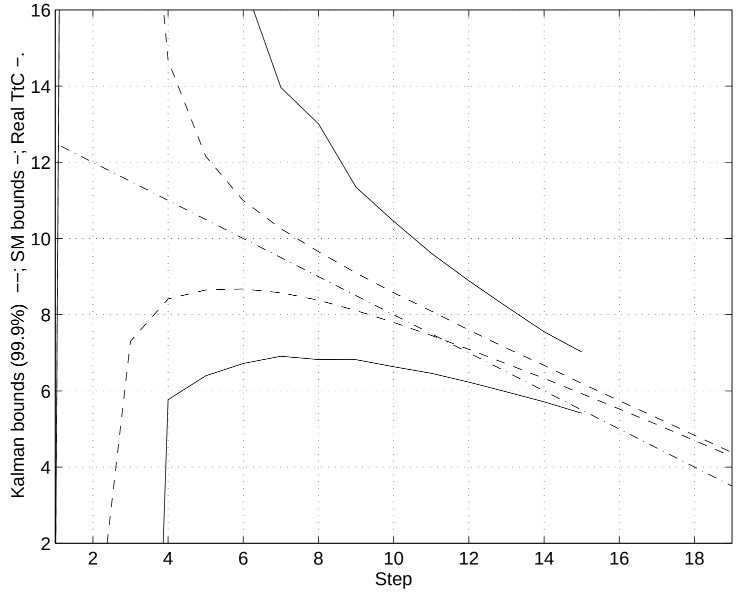
Underestimated initial ttc



Overestimated initial ttc

Comparison with Kalman filtering





Ideal setting
(exact motion model)

Realistic setting
(model errors)

SM filter detects model errors:
empty feasible set!