Robust Global Urban Localisation based on Road Maps

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6 April 2011

Motivation

- **Accurate localisation is a fundamental task in order to achieve high level of autonomy**
- **Localisation systems usually depend on GPS, but anytime-anywhere GPS positioning is not always reliable**
- **Some kind of a priori map is often available to help in the localisation process**

In this presentation

- **We present a method to perform global localisation using segment based maps together with particle filters**
- **Salient characteristics of the framework:**
  - It is able to use low quality segment-based digital maps
  - Likelihood function is generated as a grid, based on the map
  - Local history-based model is used for the observations for improving likelihood generation

Outline of this presentation

- **Background: Segment-based maps and Bayesian Localisation**
- **Approach: Constrained Localisation**
- **Experiments**
- **Conclusions and future work**

Background: Segment-based Maps

- **Some kind of digital maps are often available:**
  - Digital maps for urban positioning
- **Or they can be inferred/obtained using GIS tools:**
  - Off-road maps
  - Mining layouts
- **However, the maps might not perfect:**
  - Low quality
  - Incomplete

Background: Segment-based Maps (cont.)

- In this work we use Route Network Definition File RNDF maps (but the framework can be used for any other maps)
- Segment-based map that provides a-priori information about urban environments
- Includes GPS coordinates for location of road segments, waypoints, stop signs and checkpoints, as well as lane widths

Background: Segment-based Maps (cont.)

Background: Bayesian Localisation

- **For the robot's pose:**

$$\mathbf{x}_k = [x_k, y_k, \theta_k]^T$$

- **We aim at recursively estimate the PDF**

$$p(\mathbf{x}_k | \mathbf{z}_{1:k})$$

using a set N particles (samples and weights):

$$\{\mathbf{x}_k^i, w_k^i\}_{i=1}^N$$

Approach: Constrained Localisation

- Overview of the approach
  - Bayesian Localisation using Particle Filters
  - Constrained localisation filter that considers:

    (a) Likelihood generation based on a local grid representation of the segment-based maps (RNDF)(Basic Likelihood)

    (b) Local history-based model for the observations (Extended Likelihood)

Approach: Constrained Localisation (cont.)

- Likelihood generation (Basic Likelihood)
  - Local grid representation of the RNFD map to compute the likelihood function
  - It can efficiently generate the likelihood function for the particles in real time and minimum memory requirements
  - It can detect possible roads (segments in the RNDF map) without additional high-level evaluation of the potential candidates (multi-hypothesis handled automatically)

Approach: Constrained Localisation (cont.) → Basic Likelihood

- For a set of *N* particles $\left\{X_k^i, w_k^i\right\}_{i=1}^{N}$ we calculate the likelihood $p\left(z_k \mid X_k^i\right)$ based on a given road map as:

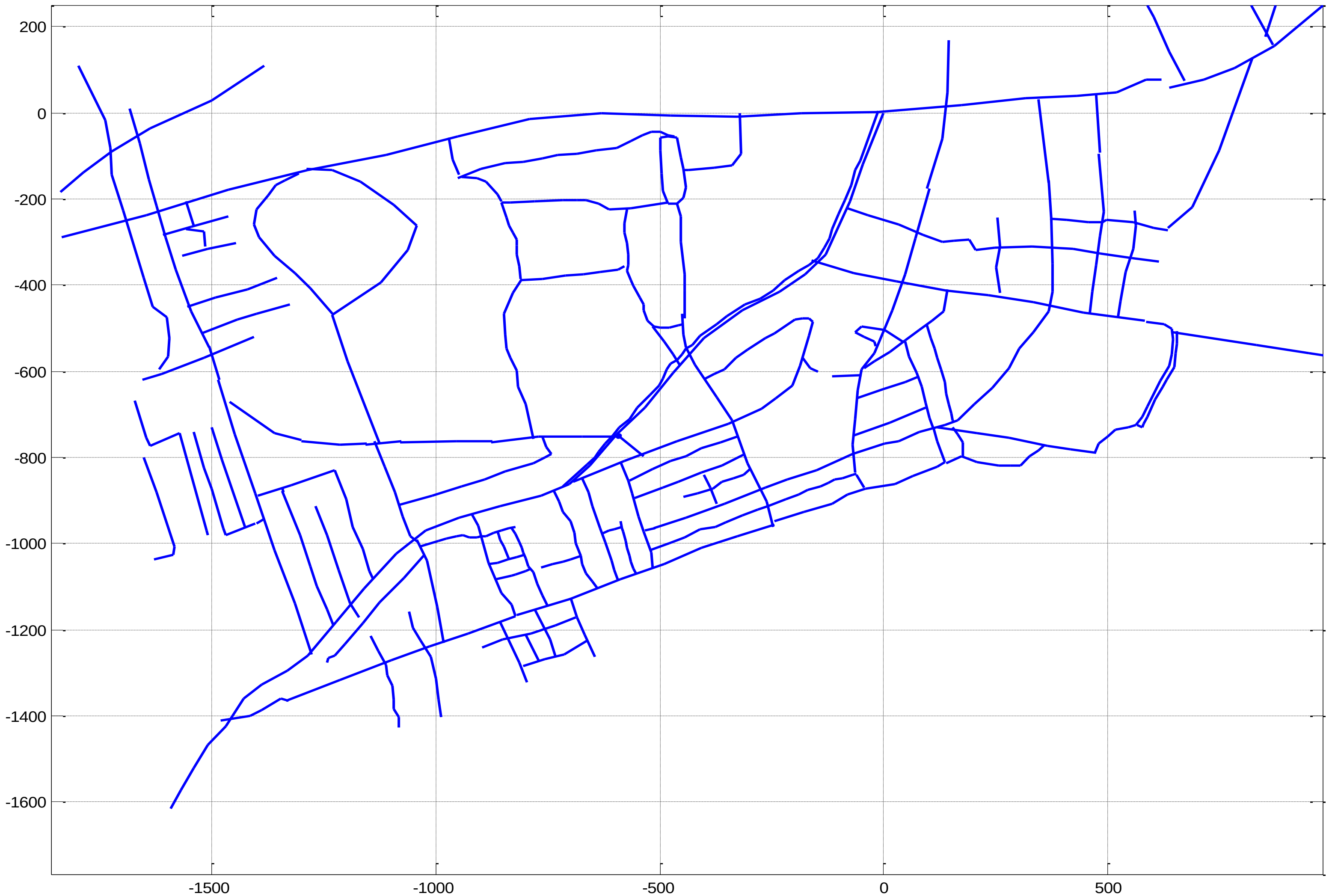
$$p\left(map \mid X\right) = \max_{j=1}^{N}\left\{f\left(X, S_j, C_j\right)\right\}$$

- Where $\left\{S_j\right\}_{j=1}^{N}$ is a set of segments that define the known road map. There are properties associated to the segments (width, lanes, traffic direction). The function *f(.)* evaluates the "distance" between a POSE and an individual segment.

- A trivial definition of likelihood is: $p\left(map \mid X\right) = \begin{cases} 1; & if \quad X \in L_{map}\left(RNDF, \Omega_k\right) \\ 0; & if \quad X \notin L_{map}\left(RNDF, \Omega_k\right) \end{cases}$

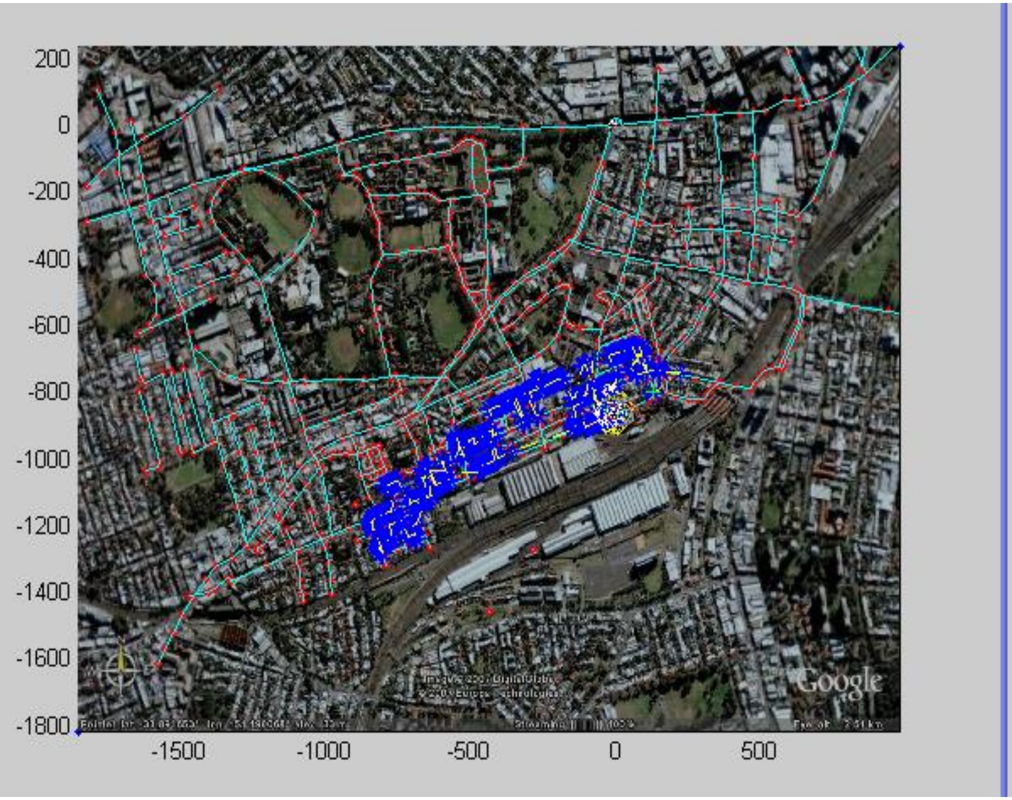
- where the region Ω_k is a convex hull that contains all the current particles and the non-convex region ***RNDF*** is defined by a set of thick bands containing the individual segments (i.e. the roads).

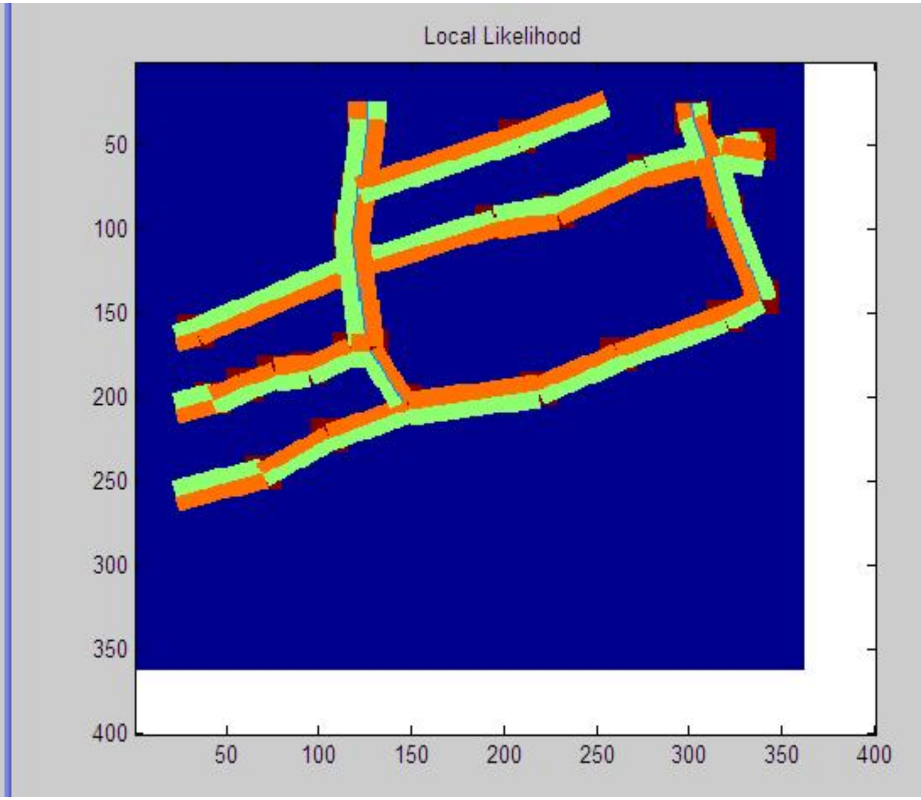
Approach: Constrained Localisation (cont.)
(full Likelihood, if the ROI was the full area)



Approach: Constrained Localisation (cont.)
(full Likelihood, if the ROI was the full area)

Example video showing local likelihood generation





Approach: Constrained Localisation (cont.) → Extended Likelihood

- Local history-based (Extended) observation model
  - “Out-of-map” navigation cases: the map can be incomplete due to non existing roads, detours, etc, or the vehicle can be actually located outside the boundaries of the map
  - Considers the recent history of the particles with a certain time horizon
  - Redefines a more convenient likelihood function based on local history

Approach: Constrained Localisation (cont.) → Extended Likelihood

- Given a particle at time *k* $X_k^i = \begin{bmatrix} x_k^i & y_k^i & \phi_k^i \end{bmatrix}^T$

  we apply dead-reckoning "in reverse" to synthesize its *hypothetical* trajectory:

$$\xi^i(t'), \quad t' \in [k-\tau, k]$$

  such that

$$\xi^i(k) = X_k^i$$

- The Extended Likelihood of the particle is now defined:

$$p^*(z_k \mid X_k^i) = \int_{k-\tau}^{k} p(z_k \mid \xi^i(t')) \cdot dt',$$

Approach: Constrained Localisation (cont.) → Extended Likelihood

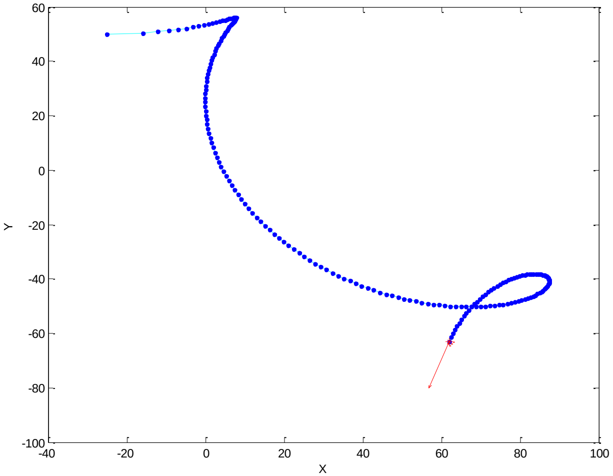
- An equivalent integral is defined over the intrinsic parameter (i.e. arc of segment) in place of the time (to make it independent of the speed).

$$p^*\left(z_k \mid X_k^i\right) = \int_0^{l_s} p\left(z_k \mid \xi^i[s]\right)\cdot ds$$

- A discrete version is applied as approximation

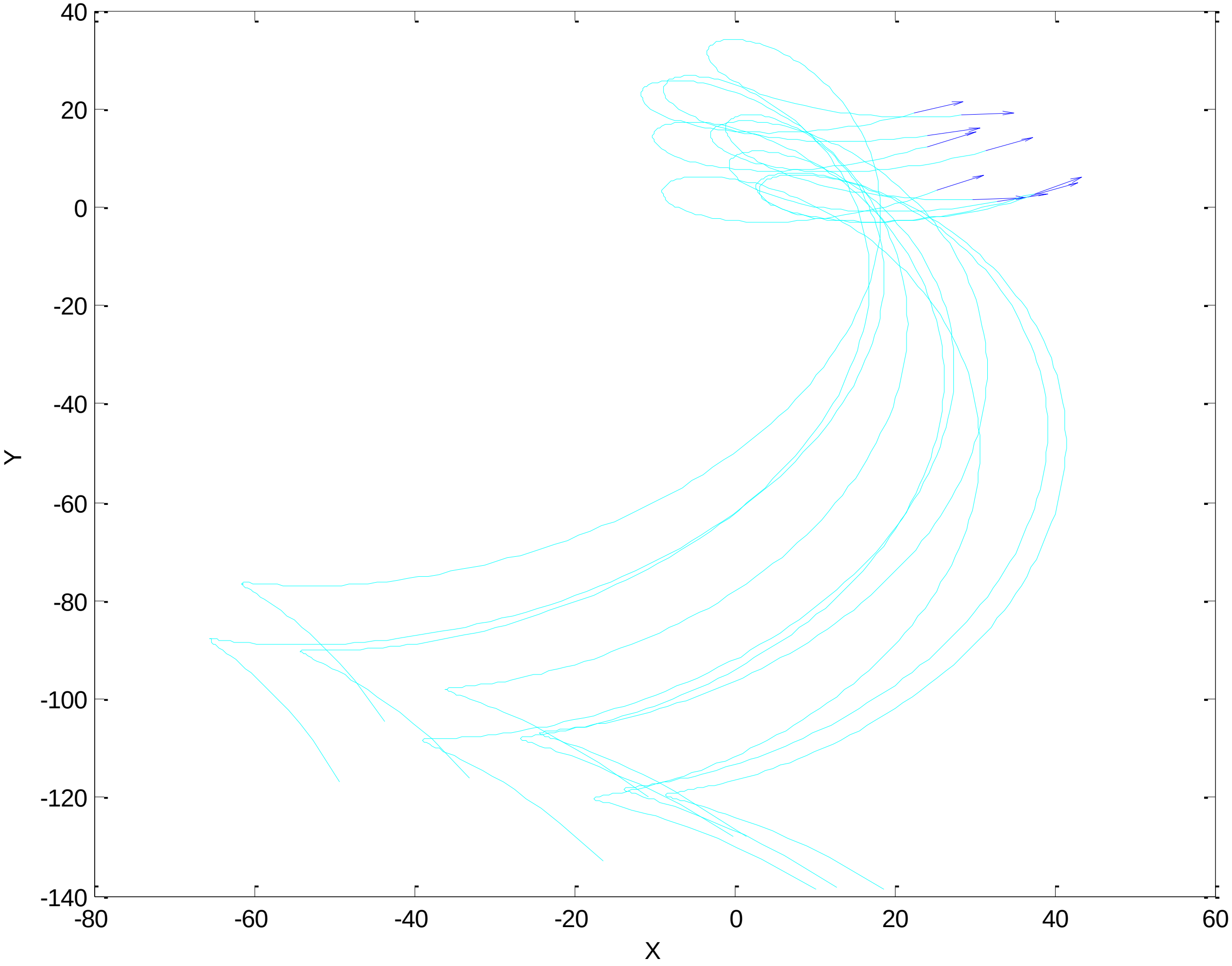
$$p^*\left(z_k \mid X_k^i\right) = \sum_{j=1}^{N_J} p\left(z_k \mid \xi^i\left[s_j\right]\right)$$

Extended Likelihood: Hypothetical Paths

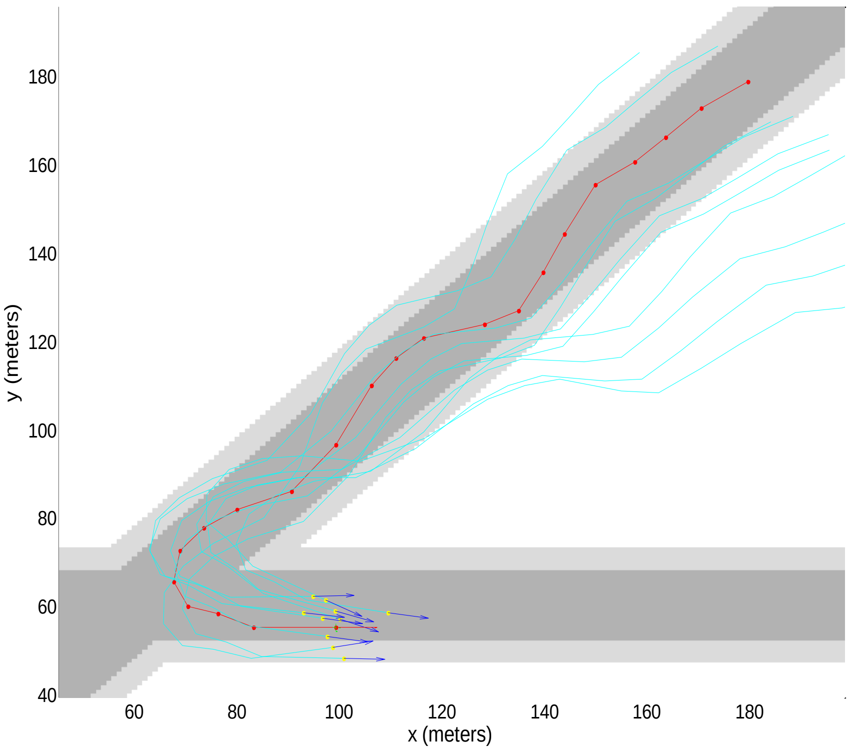


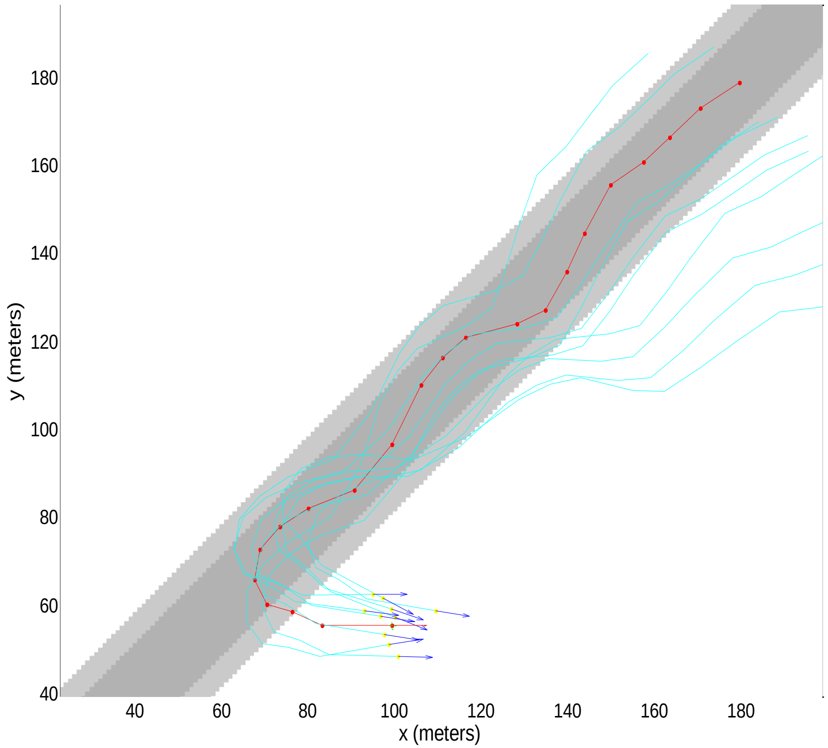
Given a Path, defined in certain Coordinate frame.

It can be associated to each particle $\left(x_k^i, y_k^i, \phi_k^i\right)$ in a different Coordinate Frame



Approach: Constrained Localisation (cont.) → Extended Likelihood





Example: In the right hand case one of the existing roads is not known, however the Extended Likelihood is still high for the "good" particles.

Approach: Constrained Localisation (cont.)

- Local history-based observation model with hysteresis
  - “Out-of-map” problem mitigated but not completely solved
  - Transition between being on the known map and going completely out of it tackled by considering hysteresis

Approach: Constrained Localisation (cont.)

- Local history-based observation model with hysteresis
- If $\max\left(p^*\left(z_k \mid X_k^i\right)\right) > K_H$

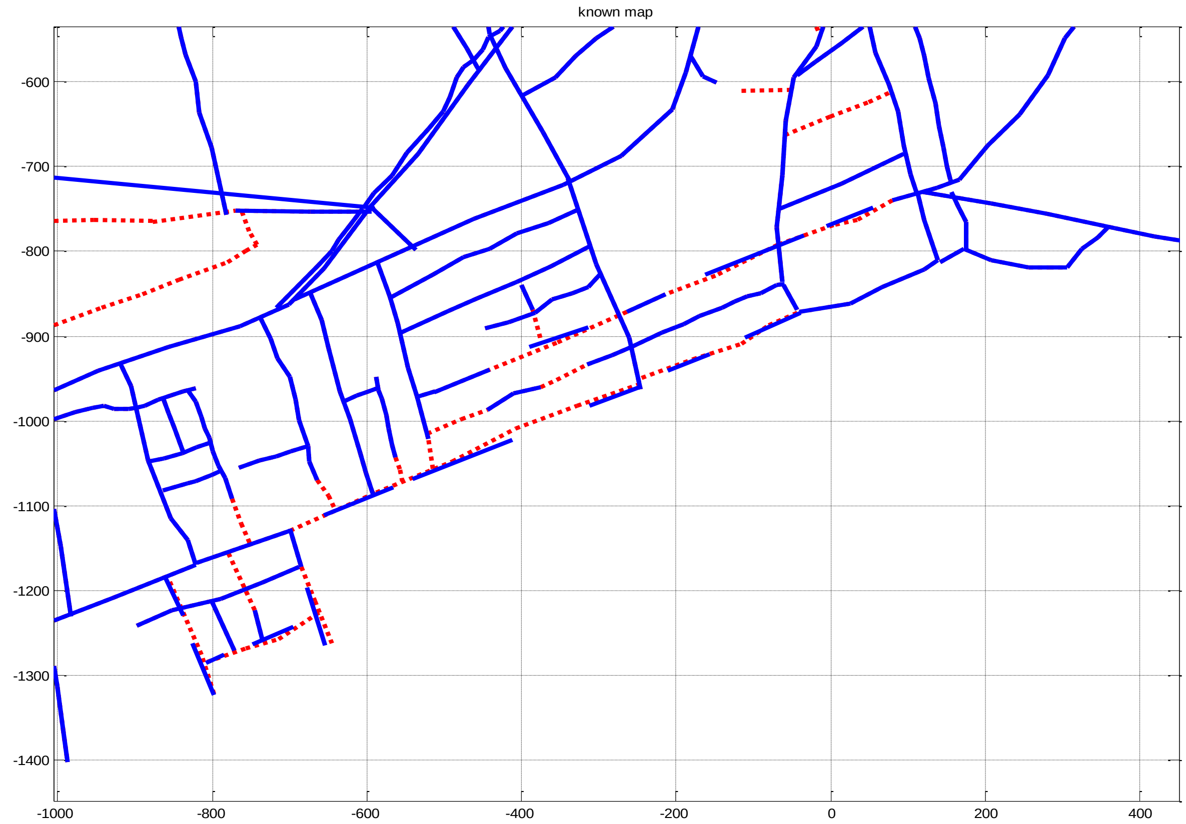
  then update particles $X_k^i \quad / \quad p^*\left(z_k \mid X_k^i\right) > K_L$

  else perform prediction only all particles

  - $0 < K_L < K_H < 100\%$
  - Typical values $K_H = 70\%$, $K_L = 60\%$

Approach: Constrained Localisation (cont.)

- Example images showing the performance of the local history-based observation model



Approach: Constrained Localisation (cont.)

- Example images showing the performance of the local history-based observation model

Approach: Constrained Localisation (cont.)

- Example images showing the performance of the local history-based observation model

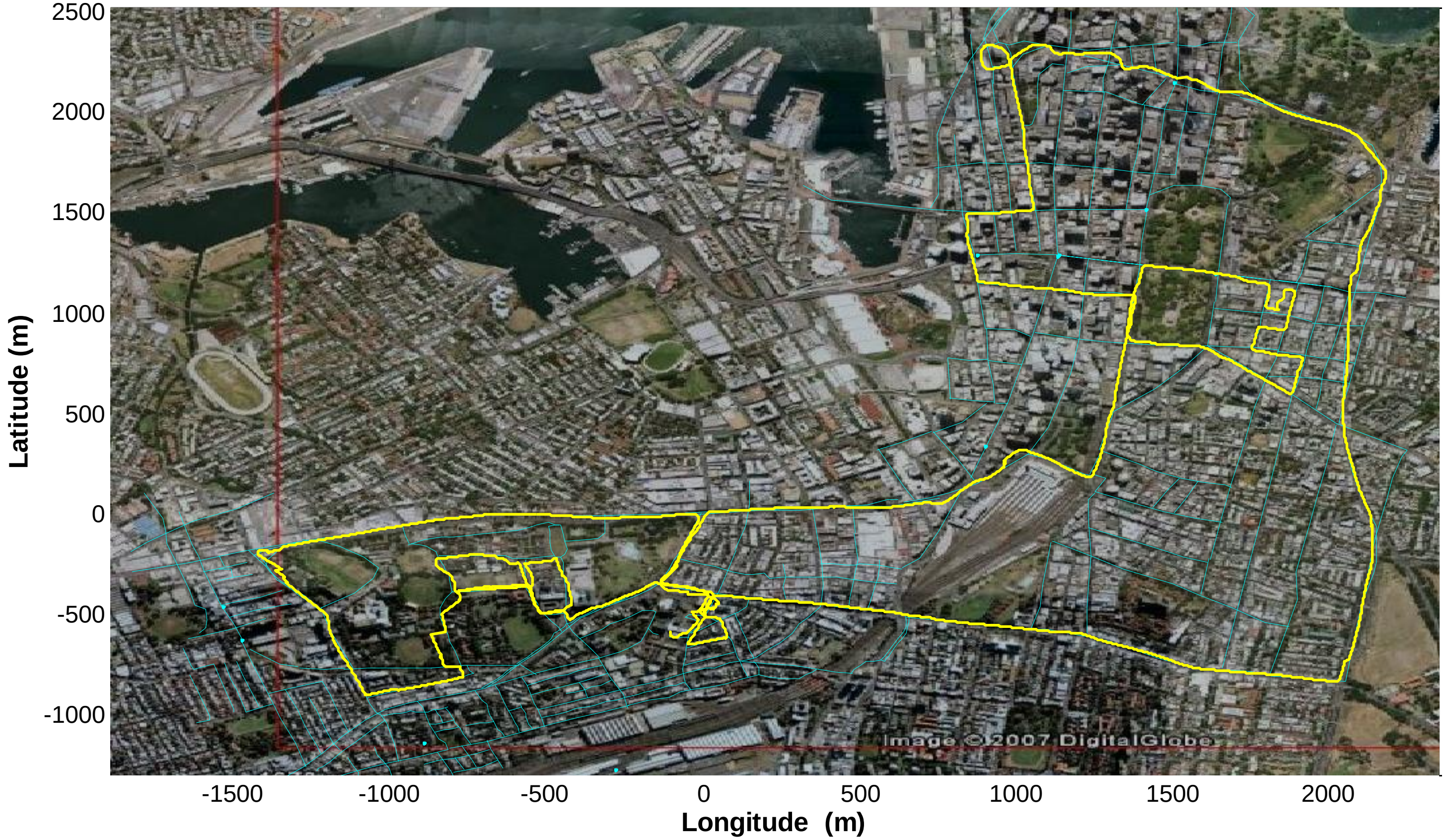
Experimental results

- More experimental results were performed, using a utility vehicle (the vehicle used in the Victoria Park Datasets).
- Vehicle motion roughly estimated using velocity encoder + low quality INS 1D gyro.

- Example video

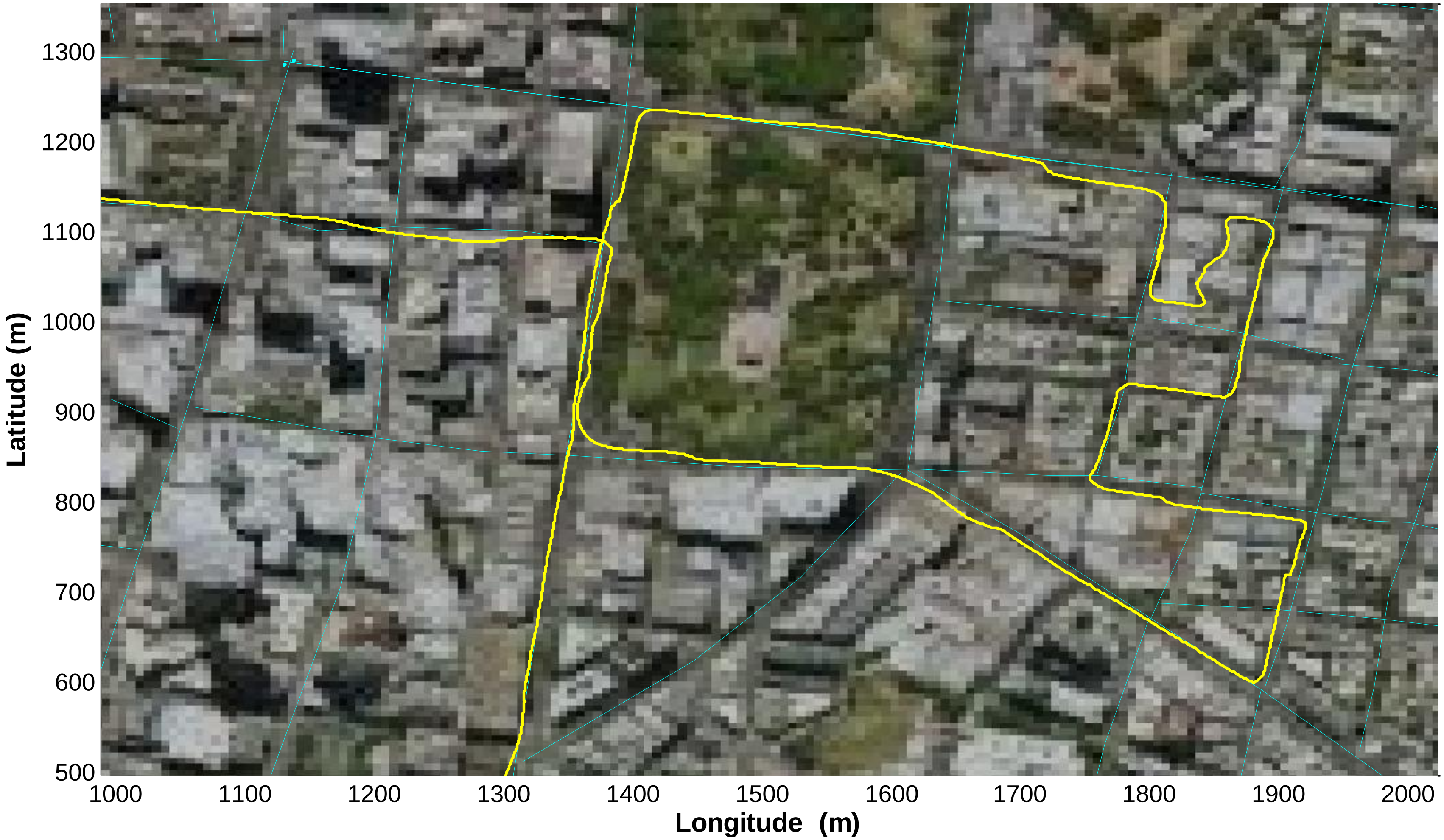
- Length of trajectory: 17km (including 2km tunnel)
- GPS shown in blue only for evaluation purposes.
- Video speed 6x actual speed.
- Final trajectory shown in yellow

Experimental results



Estimated path (in yellow) for one of the experiments. The known map (cyan) and a satellite image of the region are included in the picture.

Experimental results



A section of the previous figure where the solution is consistent even where the map is incomplete. Vehicle travelled on an unknown road (approximately x=1850m, y=1100m).

Conclusions

- Global localisation approach that fuses particle filters with low quality digital maps and can deal with out-of-road navigation situations
- Method applicable in a variety of scenarios, where some kind of map is available (not only urban, but also mines, underwater, etc)
- Neatly handles very poor quality input data

Future work

- Include lane direction
- Start from a fully unknown position
- Use other sensors (eg. Lasers) to detect intersections to improve observability on straight roads
- Add GPS or compass measurements or other sensors

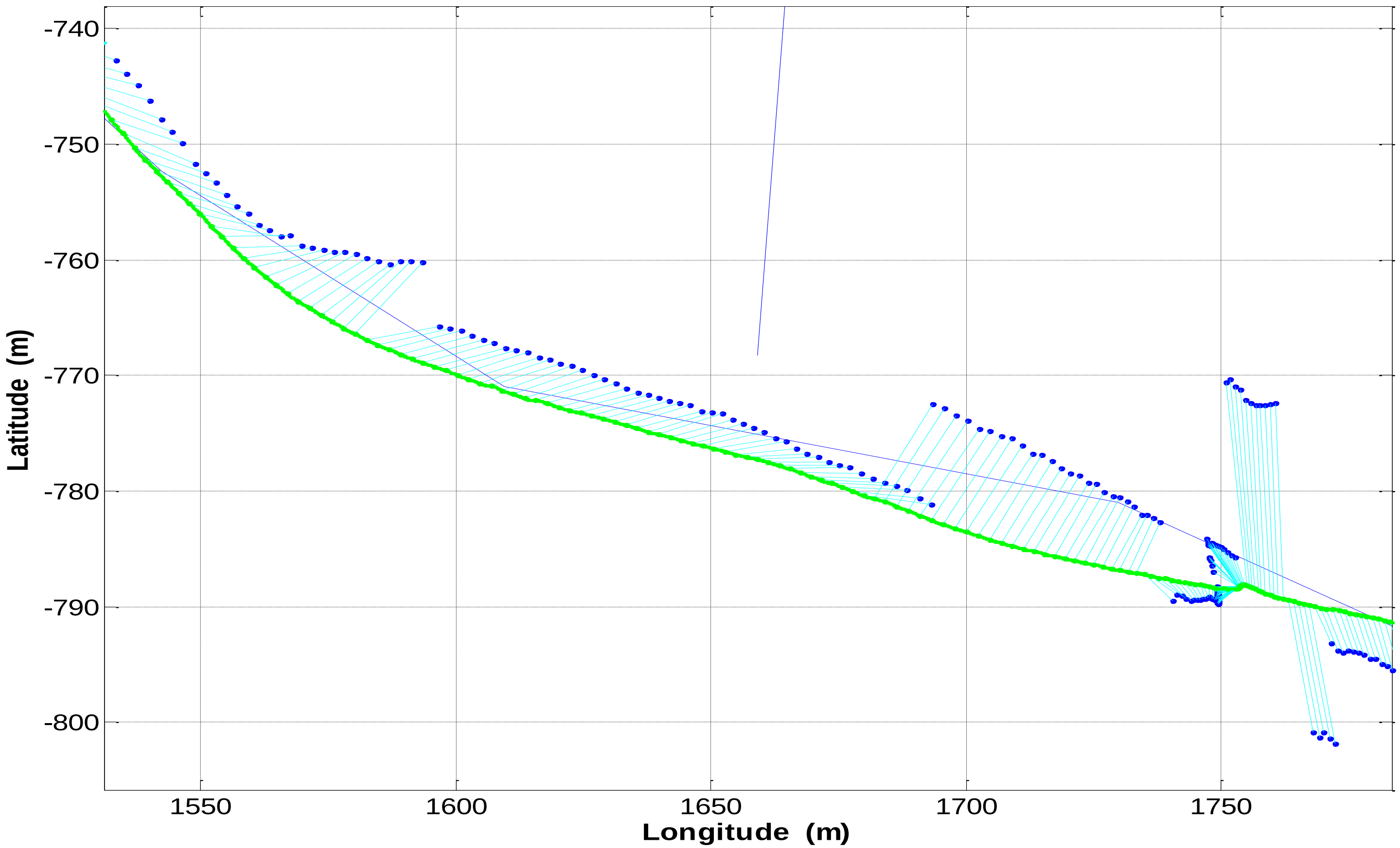
Feedback/questions

Thanks!

See www.robotics.unsw.edu.au or

http://www.youtube.com/user/UNSWMechatronics

More Test Results



A close inspection shows interesting details. The estimates are provided at frequencies higher than the GPS (5Hz). The GPS presents jumps and the road segment appears as a continuous piece-wise line (in blue), both sources of information are unreliable if used individually.