Vehicle Geolocalization

based on video synchronization

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Outline

Aims of Vehicle Geolocalization

What is Vehicle Geolocalization?

Localize the physical position of a vehicle

Applications

- navigation
- traffic management

GPS receiver

- the most employed sensor for consumer vehicle navigation and localization

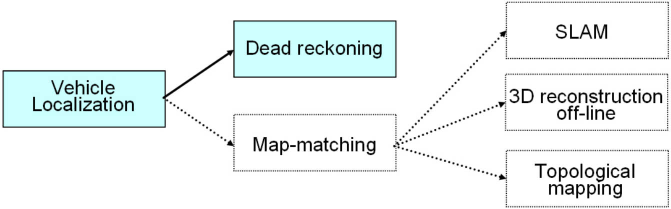
Advantages

- low cost
- easy integration
- approx. accuracy of 5–10 meters

Disadvantages

- degrade on urban scen.
  - multi–path reception
  - satellite occlusion

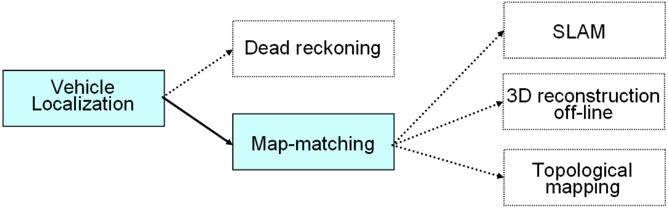
Dead reckoning



on–board inertial sensors:

- inertial measurement unit → vehicle distance travel
- gyro and compass → motion direction

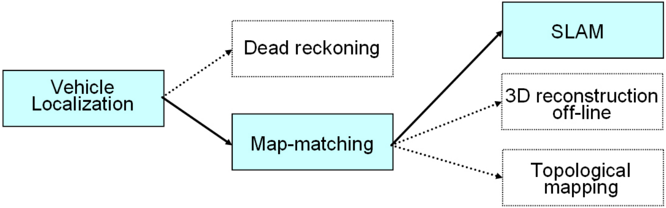
Map–matching



Vision based Map–matching

- recovers vehicle pose against an environment model to correct the vehicle localization

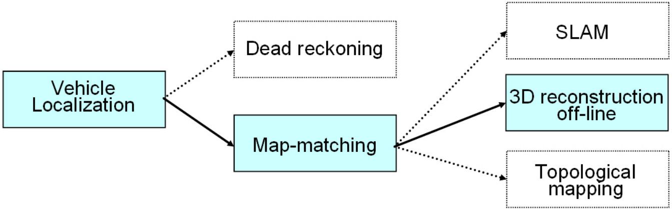
Map–Matching approaches



View–based SLAM (Dissanyake 2001)

- simultaneous localization and mapping
- on–line estimation of the environment
- extended–Kalman filter
- assumes stationary world of landmarks

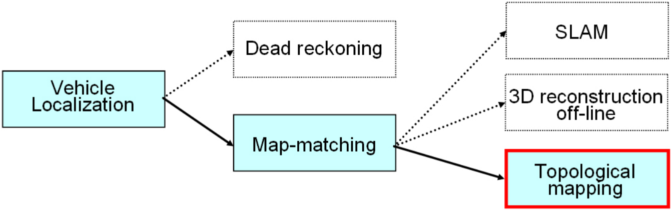
Map–Matching approaches



off–line 3D reconstruction (Levin 2004, Jun 2000)

- requires an off–line 3D reconstruction
- match the current view against the projective of map

Map–Matching approaches



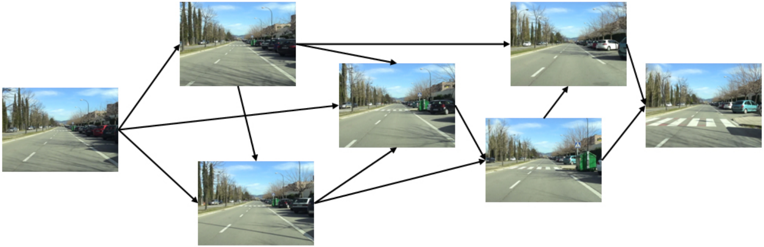
Topological mapping (Schelicher 2009, Konolige 2001, Hakeen 2006, Courbon 2009)

- topological world is estimated on–line
- add images into a database maintaining a link graph
- efficient image matching scheme against topological map

Topological mapping

Schelicher 2009

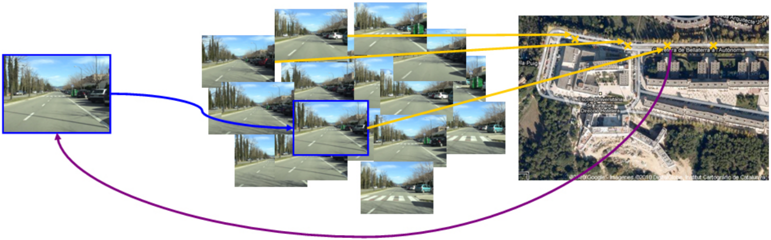
- combination of *stereo–vision* and *GPS data*
- localize a vehicle in a large–scale environment map



Topological mapping

Hakeen 2006

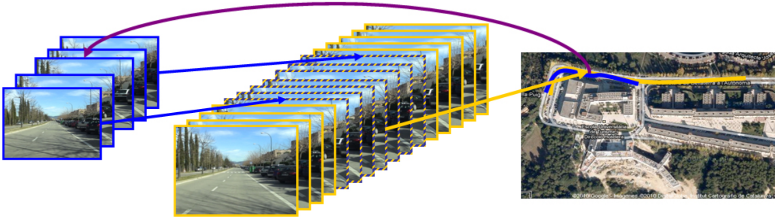
- topological map is georeferenced
- transfer the geospatial information from the topological mapping



Our goal

Geolocalize a vehicle

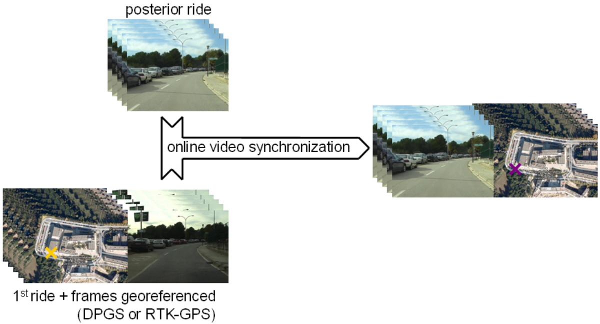
- exploiting a temporal coherence of following a planned routed



System Overview

Key idea

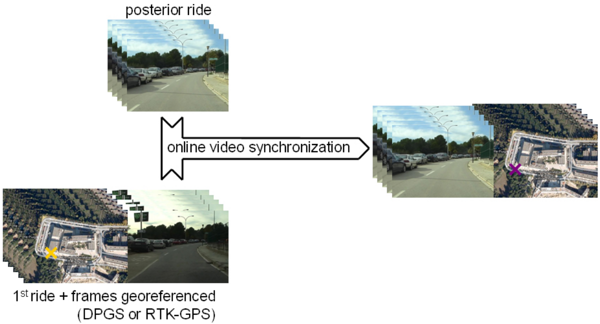
Transfer the geospatial information from a first ride into the other rides driven at different times



System Overview

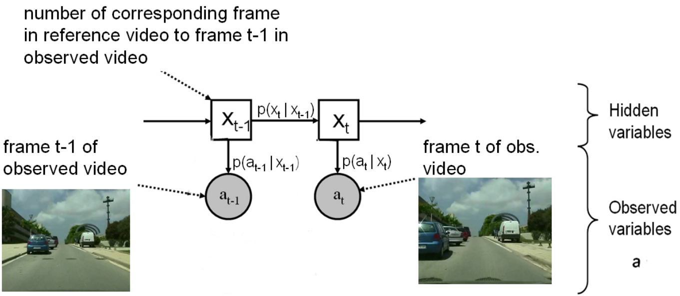
On—line video synchronization

relates the frames of the posterior ride to frames of a first ride maximizing jointly 'similar content'



On–line video synchronization

- estimate the most likely frame in a reference sequence for each newly acquired frame as a probabilistic labelling problem
- label x_{t-l} is estimated at time t based on a fixed–lag smoothing on a hidden Markov model using $L+1$ observations



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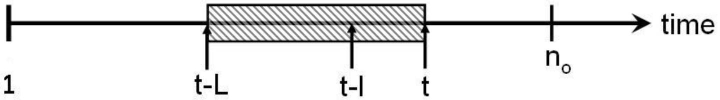

Inference using max–sum algorithm on

$$x^*_{t-l} = \underset{x_{t-l}\in\Omega_t}{\text{argmax}} \max_{\mathbf{x}_{t-L:t}\setminus x_{t-l}} p(\mathbf{y}_{t-L:t}|\mathbf{x}_{t-L:t})p(\mathbf{x}_{t-L:t})$$

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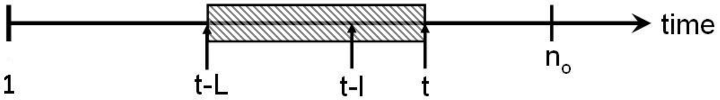

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Problem Formulation

Data term $p(\mathbf{x}_{t-L:t})$

Markovinity

$$p(\mathbf{x}_{t-L:t}) = P(x_{t-L}) \prod_{k=t-L}^{t-1} p(x_{k+1}|x_k)$$

the vehicle cannot reverse its motion direction

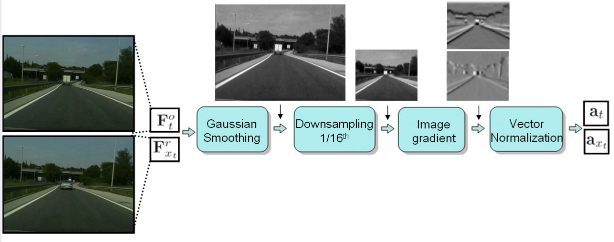
$$p(x_{k+1}|x_k) = \begin{cases} v & \text{if } x_{k+1} \geq x_k \\ 0 & \text{otherwise} \end{cases}$$

Problem Formulation

Observation term $p(\mathbf{y}_{t-L:t}|\mathbf{x}_{t-L:t})$

the observations are independent given **x**

$$p(\mathbf{y}_{t-L:t}|\mathbf{x}_{t-L:t}) = \prod_{k=t-L}^{t} p(y_k|x_k)$$



Experiments: 2 Scenarios

An scenario consist of:

- two video sequences:
  - SONY DCR–PC330E
  - 25 fps
- both sequences georeferenced as GT:
  - DGPS Trimble–GeoXT
  - 50*cm* accuracy
  - 1*Hz* output frame rate
- obs. sequence georeferenced as comparison:
  - KEOMO 16 channel
  - 1*Hz* output frame rate

Scenario description

Scenario 1

- average speed 50*kph*
- distance 1.5*km*
- length ref. and obs: 3500 and 3200 frames

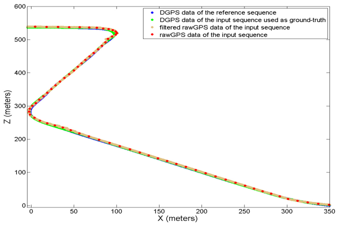
Scenario 2

- average speed 50*kph*
- distance 1*km*
- length ref. and obs: 2100 and 1800 frames

DGPS/GPS post–processing

DGPS/GPS data

- is available only in 4% of the frames
- some knowledge can be exploited → follow a regular trajectory
- Rauch–Tung–Striebel Kalman smoother → interpolate lacking data



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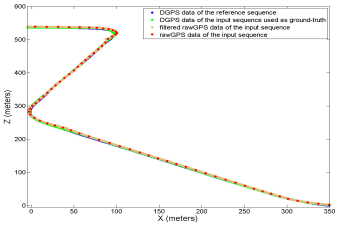

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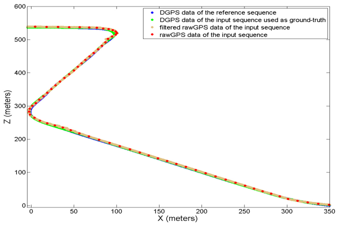
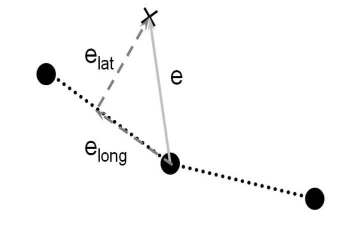


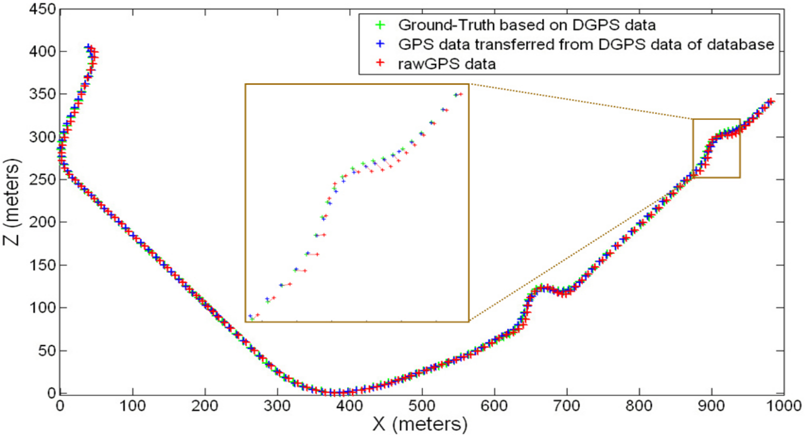
Error metric

Euclidean distance

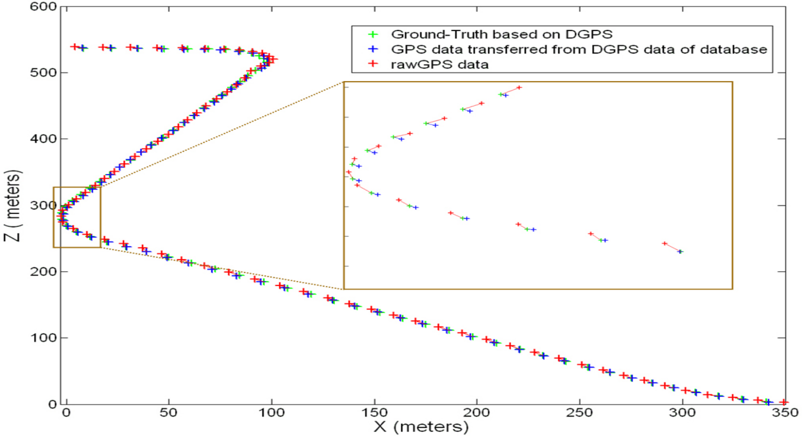


- estimated geospatial location against ground–truth
- projection of the error against the vehicle trajectory: *longitudinal* and *lateral* error

Results: Scenario 1



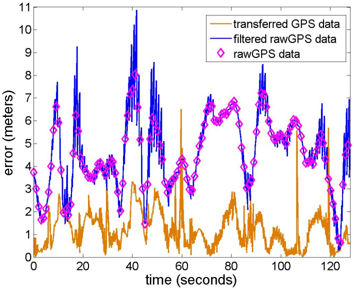
Results: Scenario 2



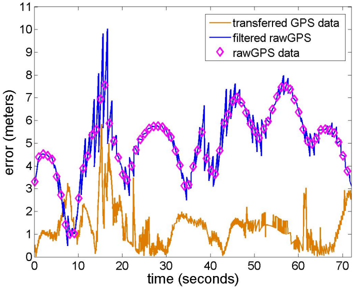
Results

- an average of 1.5 meters against 6*m* of the consumer GPS
- an accuracy less than 2 meters in 80%

Scenario 1



Scenario 2



Conclusions

1. Novel approach of vehicle geolocalization exploiting temporal coherence (planned route)
2. localize the vehicle without a GPS receiver
3. a qualified method to interpolate the unavailable GPS data
4. an accuracy average of 1.5 meters
5. available to localize in urban areas with multipath reception and satellite occlusion

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