Map-Aided Dead-Reckoning With Lane-Level Maps and Integrity Monitoring

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Localization For The Intelligent Vehicles

Knowing where the car is located

Absolute position is important
Provided by GNSS receivers

Localization alone is insufficient

Requires a digital road map
- Geographic Database
- Provides contextual information

Source: Google Maps
Road Map: a Source of Information

High accuracy road map (mesoscale)

• A good description of the road network is needed
• Lane-level descriptions
• Contextual information

From absolute localization to relative position

Map-matching process
Accuracy

**Ideal case**
- Positioning with the same level of accuracy as the map

**Actual situation**
- GNSS Positioning cannot reach the accuracy of the road map in every situation (e.g. urban environment)

**Uncertainty Characterization**
- Metrics such as Horizontal Protection Level (HPL)
- It is however insufficient to use on lane-level maps
Approach

Purpose
To improve the confidence on the positioning system estimates, using additional information from the map and vehicle odometry

Rationale
Provide a coherence metric to the positioning system, in order to determine if it can be used on lane-level road maps
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Approach

Determine a set of likely matching hypotheses

• Given the map and odometry
• With high probability:
  • The set should contain the correct solution
  • Keep all likely solutions

Assumption

The map is correct and accurate
Particle Filter Map-Matching

- GNSS fix + HPL
- Integrated sensors: Wheel Speed, Yaw Rate

1. **Initialization**
   - Particles generation around GNSS fix:
     \[ X^i = (x^i, y^i, \psi^i, ml^i) \]
   - Initial Matching:
     \[ X^i = (x^i, y^i, \psi^i, ml^i) \]

2. **Main Loop**
   - State Prediction: Unicycle model
     \[ X_t^i = X_{t-1}^i + f(v_t, \omega_t) \]
   - Matching Update
   - Weight Update: Map likelihood calculation
   - Resampling

3. **Final Steps**
   - GNSS gating
   - Matching Hypotheses
   - Ext. sens.
   - Camera
Safety-Oriented Design

Filter’s result

• Returns a set of all the likely matching hypotheses, given the map and proprioceptive information

• Experiments have shown that the set includes the correct matching hypothesis
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Assess The Coherence of the Positioning System

Inspired by Functional Safety

- Redundancy as a key element

Voting System
Sources available

On one hand: Map-Aided Odometry
- Mainly based on proprioceptive information and the road map
- Not strongly dependent on GNSS estimates

On the other hand: GNSS fix
- With covariances returned from the receiver
One multi-hypothesis source

Map-Aided Odometry

- Each hypothesis will be compared individually with the GNSS
Testing All Hypotheses: Use/Don’t Use

If no (or multiple) hypothesis remains after the test: Don’t Use

• No coherent hypothesis is found
• Or ambiguities still exist

If a single hypothesis remains after the test: Use

• All ambiguities resolved
• And coherent hypothesis

Test frequency: set on the GNSS reception (5 Hz)
Decision on hypothesis coherence

Considering GNSS and MM hypotheses as distributions

• Using covariances returned by GNSS receiver
• Or computed from the particles sets

Idea: Assess the coherence of the positioning system using these distributions
Mahalanobis Distance

Given by:

\[ D_{M,j}(\bar{X}_j) = \sqrt{ (\bar{X}_j - X_{GNSS})^T \Sigma^{-1} (\bar{X}_j - X_{GNSS}) } \]

- \( \bar{X}_j \): mean particle position (for each hypothesis)
- \( X_{GNSS} \): GNSS fix
- \( \Sigma \): sum of the covariance matrices (independence assumption)

The distance compares the characteristics of the distributions
Mahalanobis Distance

$\chi^2$ test

- Under Gaussian assumption: $D_M^2 \sim \chi^2$
Meaning of the test

If the test fails (value greater than threshold)

• Does **NOT** mean the hypothesis wrong
• Does **NOT** mean the GNSS wrong

It means that the hypothesis is not coherent with the GNSS fix

Something is wrong
No matter what, this hypothesis should not be used
Different Situations

Varying dispositions

- Correct Hypothesis
- Other Hypothesis
- GNSS Fix
Testing All Hypotheses: Use/Don’t Use

Results

<table>
<thead>
<tr>
<th>%</th>
<th>Don’t Use</th>
<th>Correct Use</th>
<th>Incorrect Use</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>33.9</td>
<td>65.6</td>
<td>0.5</td>
</tr>
</tbody>
</table>

![Diagram showing use and don’t use over time]

- Use Good
- Use Wrong
- Don’t Use
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Conclusion

Developed a Map-Aided Odometry

• Multi-hypothesis map-matching, using a particle filter
• Minimal use of GNSS, only with an HPL

Coherence checking of the positioning system

• Use/Don’t Use Classification
• Using Mahalanobis Distance

Application: Learning maps

• Add information about the positioning quality at a given place
Thank you for your attention