LiDAR SLAM Utilizing Normal Distribution Transform and Measurement Consensus

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Simultaneous Localization and Mapping (SLAM)$^{[1][2]}$

- Simultaneously map environment and localize robot in it
  - Match new measured point clouds to previous reference
  - Update map with landmarks from new point clouds
- Iterative Closest Points (ICP)$^{[3]}$ commonly used for LiDAR scan matching
  - Scan matching yields pose to match test (new) and reference ranging measurements

[2] Zhang et al. RSS 2014
[3] Segal et al. RSS 2009
Point Cloud Approximations

• Real-time LiDAR SLAM for smaller platforms requires point cloud representations with:
  ▪ Low map storage
  ▪ Fast global matching

• Parametric point cloud approximations,\(^{[4],[5]}\) such as Normal Distribution Transform\(^{[6]}\), reduce map storage requirements\(^{[7]}\)

![Diagram showing point cloud approximations](https://via.placeholder.com/150)

- \(n\) points measured in a 2D cell.
- \(n\) points, \(2n\) parameters
- Gaussian approximation for the 2D cell.
- 1 distribution, 5 parameters

[5] Dhawale et al. CVPR 2018
Normal Distribution Transform (NDT)$^{[8],[9]}$

- In NDT, the 3D field of view of a point cloud is divided into voxels.
- Points measured in each voxel are approximated by a 3D Gaussian distribution.
- Voxel edge length of 50cm captures feature detail in example.

$^{[8]}$Biber et al. IROS 2003
$^{[9]}$Takeuchi et al. RSJ 2006

Voxel edge length tuneable to reduce parameters while capturing feature detail.
For high reliability localization solutions, we need to:

- Eliminate potential high-fault steps from scan matching pipeline
- Reduce impact of feature-level LiDAR faults such as outliers and occlusions
- Quantify impact of feature distribution on overall localization reliability\(^{10}\)

Prior Work:
- Quantifies probability of hazardously misleading information for ICP\(^{11}\)
- Overbounds localization solution by quantifying feature-match uncertainty\(^{12}\)

Planes introduce parallel uncertainty. Different configurations of same planes result in different localization uncertainty.

\(^{10}\) Shetty & Gao, ION ITM 2017
\(^{11}\) Larson, Tech. Rep. AFIT 2010
\(^{12}\) Joerger & Pervan PLANS 2016
Localization using Reliable Features

- Potentially faulty measurements given same weight as non-faulty in most scan matching algorithms
- Optimizing with only reliable features can reduce convergence time
- Reliable features will have consistent measurements across time
- Consensus can estimate consistency of feature measurements

Measurement consensus can be used to detect and remove potential faults
Objectives

• Design NDT SLAM architecture that reduces impact of feature-level faults on scan matching pipeline

• Quantify reliability of localization and mapping solution

• Perform experimental validation using real-world data
  ▪ Benchmark localization performance against naïve NDT SLAM
  ▪ Validate localization reliability metric formulation
Outline

• Consensus-NDT SLAM

• Measurement Consensus Metric
  ▪ Voxel Consensus Metric
  ▪ Localization Consensus Metric

• Experimental Verification
  ▪ Localization and Mapping Results
  ▪ Consensus Metric Verification

• Conclusions
NDT SLAM

- LiDAR odometry for each pair of consecutive point clouds
- Map update performed once every keyframe
  - Keyframe: Point clouds measuring same physical space

![Diagram of NDT SLAM process](image)
Consensus-NDT SLAM: LiDAR Odometry
Consensus-NDT SLAM: Map Update

Prior map → Retain high consensus voxels → Mapping optimization → Posterior map

Current keyframe → Localization consensus metric

Final LiDAR poses
Consensus-NDT SLAM: Advantages

• NDT SLAM:
  - Feature correspondence step eliminated
  - Odometry and Mapping objective function piecewise continuous
  - Odometry Jacobian and Hessian have analytical expressions
  - Map updates matches point clouds in keyframe to map and each other

• LiDAR Odometry:
  1. Pose evolves rapidly over initial optimization iterations for given test-reference pair
  2. Coarse estimate utilized to remove potentially faulty voxels
  3. Reduced computational load and faster convergence time

• Map Update:
  - High consensus voxels used as map landmarks
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Consensus Metric Relationship

- **Voxel consensus metric:**
  - Test point cloud transformed using candidate pose
  - Feature-level measurement consensus quantified using transformed point cloud for each voxel in NDT reference
- **Localization consensus metric:**
  - Combines all voxel consensus metrics for given candidate pose
  - Estimates total measurement consensus supporting candidate pose for test-reference pair
Voxel Consensus Metric ($C_v$) (1)

- Quantify goodness of match on feature-level irrespective of voxel characteristics
- Use a smooth normalized voxel consensus metric ($C_v$)
  1. Calculate Residual Sum of Squares (RSS) for each voxel
  2. Scale and shift RSS using hyper-parameters $\tau_{\text{high}}$ and $\tau_{\text{low}}$
  3. Use sigmoid for smooth normalization of result

$C_v$ v RSS for a voxel with 6 measured points, indicating intervals in the RSS of high and low measurement consensus
Voxel Consensus Metric ($C_v$) (2)

- Simulated example indicates negative correlation of $C_v$ to presence of fault in voxel

- Example measurements with fault are shown alongside reference Gaussian distribution approximating feature
Localization Consensus Metric \( (C_m) \)

- Clusters of low consensus voxels can cause localization drifts
- Similar to \( C_v \), require a normalized metric to quantify feature distribution in LiDAR FOV
  
  1. Calculate Consensus Weighed Dilution of Precision (CWDOP)
  2. Smooth normalize using DOP
- Simulated 2D data shows that the clustering of low consensus voxels is reflected in \( C_m \)

\[ \text{(a) Spread Out Voxels: } \quad C_m = 0.66 \]
\[ \text{(b) Clustered Voxels: } \quad C_m = 0.44 \]
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Localization Dataset

• Dataset must contain challenging feature distribution
  ▪ Noisy sparse points from objects like vegetation
  ▪ Parallel planes and edges increase uncertainty

• Point clouds collected on UIUC campus used for localization test
Localization Results

- Consensus-NDT SLAM results in fewer iterations and faster convergence

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Iterations per point cloud pair</th>
<th>Time per point cloud pair</th>
<th>Time per iteration (coarse optimization)</th>
<th>Time per iteration (fine optimization)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consensus-NDT SLAM</td>
<td>20</td>
<td>110 s</td>
<td>7 s</td>
<td>1 s</td>
</tr>
<tr>
<td>Naïve NDT SLAM</td>
<td>28</td>
<td>196 s</td>
<td>7 s</td>
<td>7 s</td>
</tr>
</tbody>
</table>

- Accuracy is maintained compared to naïve NDT SLAM

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$\Delta x$</th>
<th>$\Delta y$</th>
<th>$\Delta z$</th>
<th>$\Delta \phi$</th>
<th>$\Delta \theta$</th>
<th>$\Delta \psi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consensus-NDT SLAM</td>
<td>7.6 cm</td>
<td>7.4 cm</td>
<td>1.4 cm</td>
<td>0.13°</td>
<td>0.14°</td>
<td>0.38°</td>
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<tr>
<td>Naïve NDT SLAM</td>
<td>7.8 cm</td>
<td>7.3 cm</td>
<td>1.8 cm</td>
<td>0.15°</td>
<td>0.14°</td>
<td>0.40°</td>
</tr>
</tbody>
</table>
Consensus Dataset

- Dataset must contain reliable ground truth estimates
  - Independent rotation and translation ground truth estimates required
- Point clouds from the KITTI Vision Benchmark Suite\(^{[10]}\) used for consensus verification
- Validation performed with point cloud from previous time instant as reference

KITTI sensor setup\(^{[10]}\)
Consensus Results: Voxel (1)

Original NDT approximation of reference point cloud

NDT approximation with points shaded according to $C_v$ from the corresponding voxel

Sparsely detected objects

Dynamic objects

Voxel consensus metric low for moving and sparsely detected objects
Consensus Results: Voxel (2)

Local plot of reference (pink) and test (cyan) point clouds

Mismatch

Low $C_V$

Reference points shaded by their $C_V$, black indicates a low value

Voxel consensus metric detects feature mismatch in this example
Consensus Results: Localization

Variation in $C_m$ with translational deviation (along x-axis) from ground truth

Variation in $C_m$ with rotational deviation (along roll) from ground truth

$C_m$ decreases with increase in deviation from ground truth
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Conclusions

• Proposed Consensus-NDT SLAM architecture with faster convergence and lower computational load

• Used voxel consensus metric to detect and remove potential feature-level faults from the scan matching pipeline

• Quantified navigation reliability by means of localization consensus metric

• Validated localization performance and consensus metric formulation using real-world datasets
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Thank you!
References

References (2)


