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Proximal pose search for adapting SLAM in dynamic environments on slow moving UGVs

AIM

Precise localization of slow moving UGV in dynamic environment like crowded manufacturing factories[1] for long term SLAM

SYSTEM SETUP

Custom designed UGV by Ati Motors:

- **Desktop grade CPU w/ GPU**
- **Sensor suite:**
  - **one VP-16 Lidar**
  - **one stereo camera**
  - **sonar sensors for obstacle avoidance**

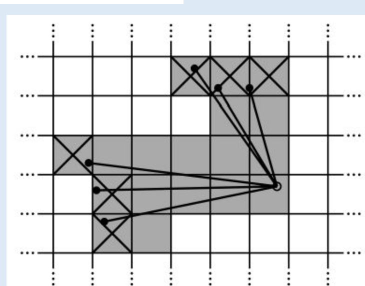
LIDAR-BASED SLAM

- **Google's Cartographer[4] performs state of the art lidar based SLAM[5],[6] and primarily consists of:**
  - **Local SLAM** : Scan matching of lidar scans to submaps get pose estimates (ξ) [7]

(In 2d setting) We find the pose $\boldsymbol{\xi} = (\mathbf{p_x}, \mathbf{p_y}, \boldsymbol{\psi})$ by

$$\boldsymbol{\xi}^* = \underset{\boldsymbol{\xi}}{\operatorname{argmin}} \sum_{i=1}^{n} [1 - M(\mathbf{S}_i(\boldsymbol{\xi}))]^2$$

$\mathbf{S_i(\xi)}$ are the ξ-transformed coords of lidar points $(\mathbf{s_{i,x}}, \mathbf{s_{i,y}})$
$\boldsymbol{M(P^m)}$ is occupancy value of a point $\boldsymbol{P^m}$ in a map, given by bicubic interpolation



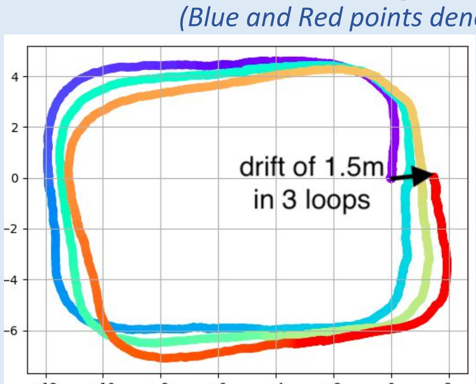
Hits (crossed) & Misses (shaded only) [Fig. 1]

  - **Global SLAM** : Correct for drift using Sparse Pose Adjustment[10]

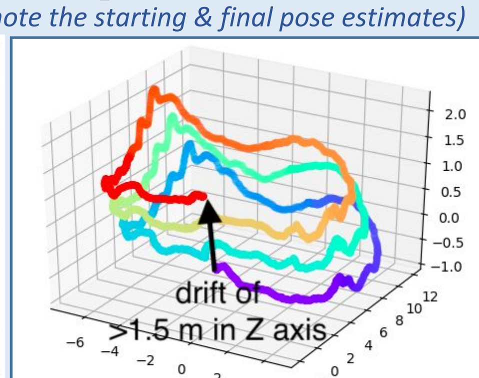
CHALLENGES

- **Localization of UGV in dynamic environment drifts with time (It is wrong about its position in env.)**

(Blue and Red points denote the starting & final pose estimates)



[Fig. 2] *UGV performs three simple square loops in 2D.*



[Fig. 3] *False detection of vehicle motion along Z axis*

  - **Significant drift -> faulty Path Planning -> accidents in factory**
- **Long term mapping is an open research challenge[8][9]**

GRID BASED PROXIMAL POSE SEARCH

We propose to search for the pose in the grid with max correspondence score:

Using robust point matching[11], we can find $\xi = (p_x, p_y, \psi)$ by :

$$\xi^* = \underset{\xi}{\operatorname{argmin}} \sum_{j=1}^{m}\sum_{i=1}^{n} \mu_{ij}\|P_j^{map} - S_i(\xi)\|^2 + g(\xi) - \alpha \sum_{j=1}^{m}\sum_{i=1}^{n} \mu_{ij}$$

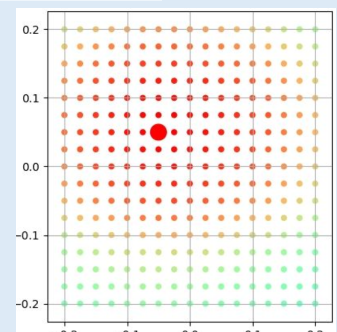
where, $\mu_{ij} = \begin{cases} 1, & \text{if } P_j^{map} \text{ corresponds to } S_i(\xi) \\ 0, & \text{otherwise} \end{cases}$

$g(\xi)$ is regularizing function and
α biases towards stronger point correspondence

Simplifying it, we can find $\xi^* = \underset{\xi}{\operatorname{argmax}} \sum_{j=1}^{m}\sum_{i=1}^{n} \mu_{ij}(\xi)$

such that $\xi = \{ (p_x, p_y, \psi) : S^q \times S^q \times S^q \}$
and $S = \{ a + (t-1)d \ \forall \ t = 1,\dots,q \}$

also, $\mu_{ij} = \begin{cases} 1, & \text{if } \|P_k^{map} - S_i(\xi)\| < \delta \\ & \text{for } k = \operatorname{argmin}_j \|P_j^{map} - S_i(\xi)\| \\ 0, & \text{otherwise} \end{cases}$

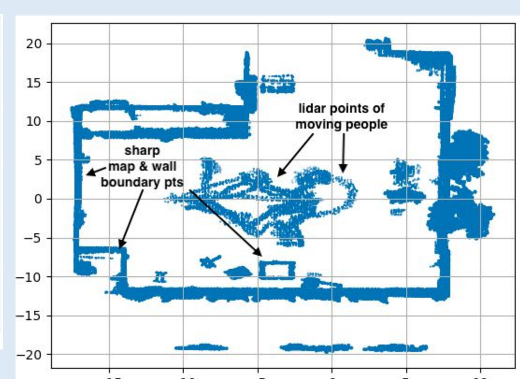


Grid point with max scan matching score gives next pose [Fig. 3]

EXPERIMENTAL RESULTS

We run our method on the same dataset to get the following pose estimates and map

[Fig. 4] *We see better poses estimates compared to [Fig. 2]*



[Fig. 5] *Top view of 3D map generated*

FUTURE WORK

- Better optimization techniques for Faster search of optimal pose
- Better scoring functions for peaked scoring grid landscape
- Applying loop closures (Global SLAM) for long term consistency
- Segmenting and separately handling dynamic points in the map
- Ability to initialize anywhere in a given map on reset

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If you have reached here, scan the QR code for references, related videos and much more.

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