Formally Correct Deep Perception For Cyber-Physical Systems

LiDAR localization with guarantees

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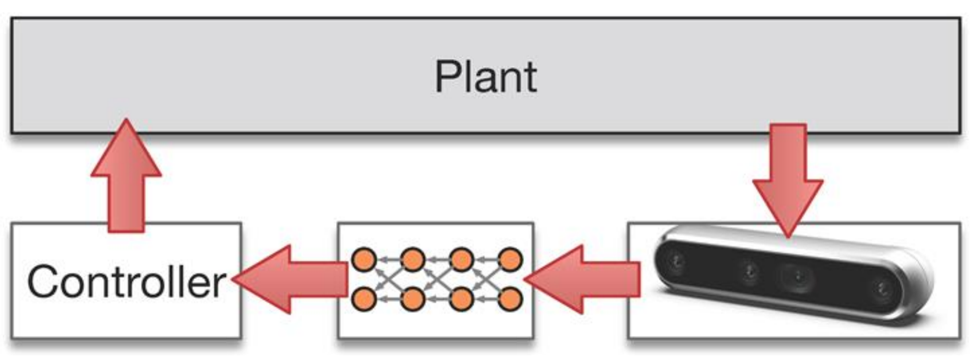
2025 Cyber-Physical Systems Principal Investigators' Meeting
March 13-14th, 2025

Context

- The **perception** pipeline of autonomous systems increasingly relies on deep learning methods, that provide **no formal guarantees** of correctness or performance.



- We aim to provide such guarantees, in two possible ways:
  - proving **deterministic worst-case bounds** on learning models;
  - using a **supervisor** to correct the learning method when needed
- Meeting our goals will have major impact by:
  - boosting the adoption of **provably safe** autonomous cars, UAVs, and other autonomous platforms.
  - **reducing risks** associated with existing autonomous vehicles
  - introducing a new graduate course on the **intersection of learning and control**.

Problem

- **Point cloud registration** (relating two LiDAR scans from different poses) is a key step in localization/SLAM.
- We want a reliable way to perform ***global*** registration. I.e., no "good initialization" should be required for correctness.
- Existing algorithms are ***local*** and need point correspondences, which may not exist in LiDAR point clouds.
- Old PASTA algorithm requires a convex environment to provide bounds, which limits its usability.

Old PASTA

- We previously developed a registration algorithm named **PASTA** [1,2] (Provably Accurate Simple Transformation Alignment).
- It is **fast** and comes with worst-case **guarantees**.

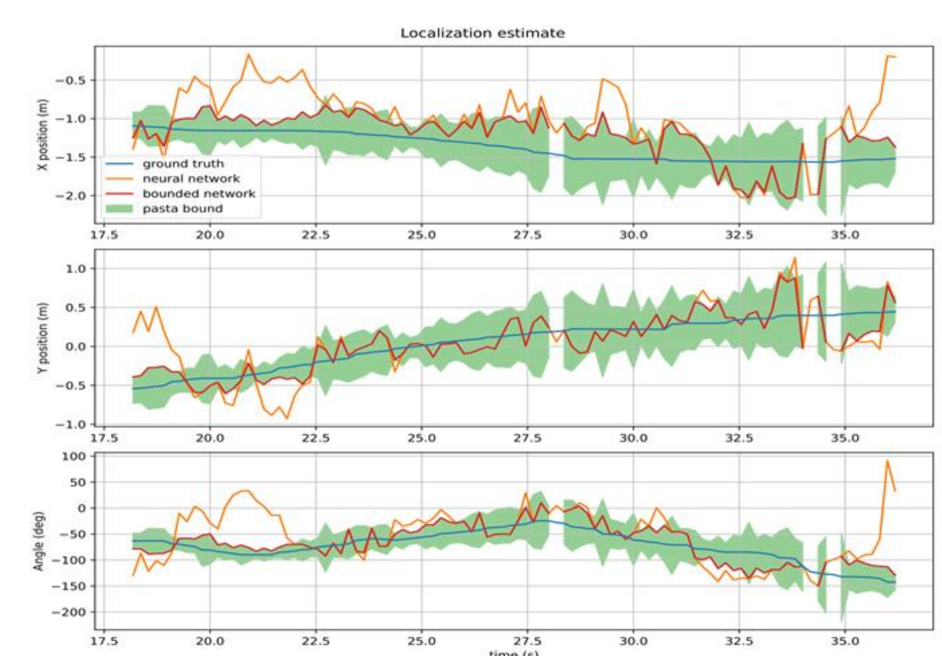
Algorithm 1 PASTA

Input: Point clouds $\{\mathbf{r}_1^{(i)}\}_{i=1}^{m_1}$, $\{\mathbf{r}_2^{(i)}\}_{i=1}^{m_2}$
Output: Transformation $\hat{\mathbf{R}}, \hat{\mathbf{p}}$
  for each point cloud i **do**
    $H_i \leftarrow$ convex hull of $\{\mathbf{r}_i^{(j)}\}_{j=1}^{m_i}$
    $\mathbf{c}_i, \mathbf{\Sigma}_i \leftarrow$ first and second moments of H_i
  end for
  $\hat{\mathbf{R}} \leftarrow$ closed-form solution of $\mathbf{\Sigma_2} = \mathbf{R}\mathbf{\Sigma}_1\mathbf{R}^T$
  $\hat{\mathbf{p}} \leftarrow$ closed-form solution of $\mathbf{c}_2 = \mathbf{R}\mathbf{c}_1 + \mathbf{p}$

[1] M. Marchi, J. Bunton, B. Gharesifard, P. Tabuada. "LiDAR Point Cloud Registration with Formal Guarantees." IEEE 61st Conference on Decision and Control. 2022.
[2] M. Marchi, J. Bunton, Y. Gas, B. Gharesifard, P. Tabuada. "Sharp Performance Bounds for Pasta". IEEE Control Systems Letters. 2023.

Old PASTA Supervised Neural Network

- We train a **neural network** to perform localization using point clouds as input, and test it on the trajectory data we collected.



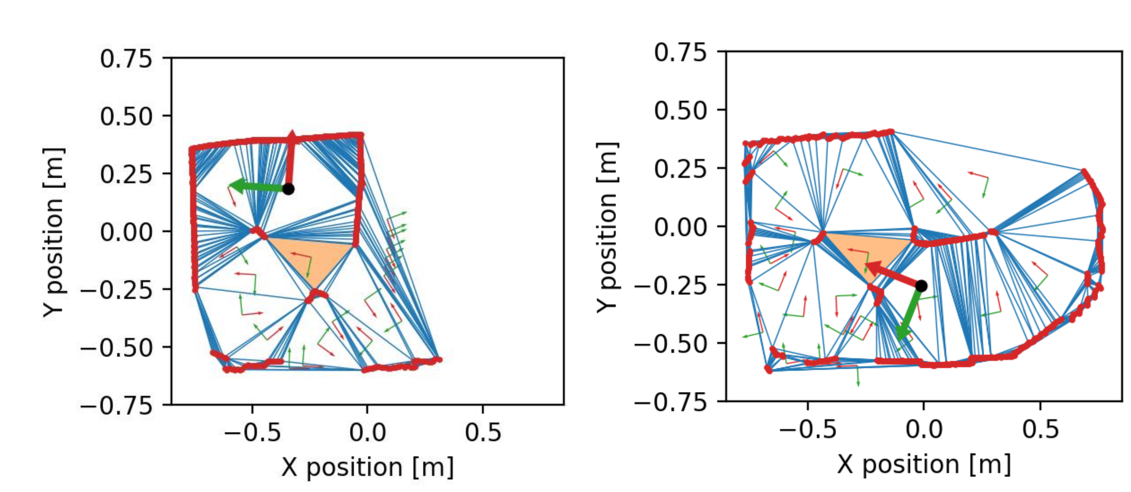
- Old PASTA and its bound act as a **supervisor** for the neural network.
- The neural network has good average performance, but sometimes behaves poorly. The **old PASTA supervisor bounds the network's output**, maintaining a limited worst-case error.

Triangle PASTA

- We developed Triangle PASTA to extend the old PASTA to non-convex environments, using triangles to find common areas in both scans (highlighted in orange).
- The overlapping areas in both scans are passed to old PASTA to estimate the roto-translation and calculate bounds error bounds

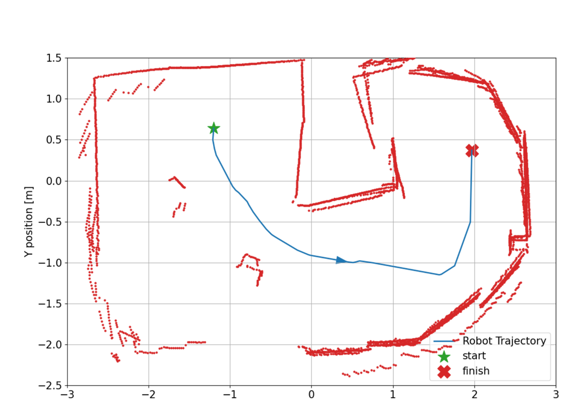
Algorithm 1 Triangle PASTA

Input Point clouds $\{r_1^{(i)}\}_{i=1}^{m_1}$, $\{r_2^{(i)}\}_{i=1}^{m_2}$
Output Transformation $\mathbf{R}, \hat{p}$
  $T_1 \leftarrow$ triangulation of $\{r_1^{(i)}\}_{i=1}^{m_1}$
  $T_2 \leftarrow$ triangulation of $\{r_2^{(i)}\}_{i=1}^{m_2}$
  $(M_1, M_2) \leftarrow$ matched triangles points
  for i=1,2 **do**
    $H_i \leftarrow$ convex hull of M_i
    $c_i, \Sigma_i \leftarrow$ first and second moments of H_i
  end for
  $\hat{R} \leftarrow$ closed form solution of $\Sigma_2 = R\Sigma_1 R^\intercal$
  $\hat{p} \leftarrow$ closed form solution of $Rc_1 + p$



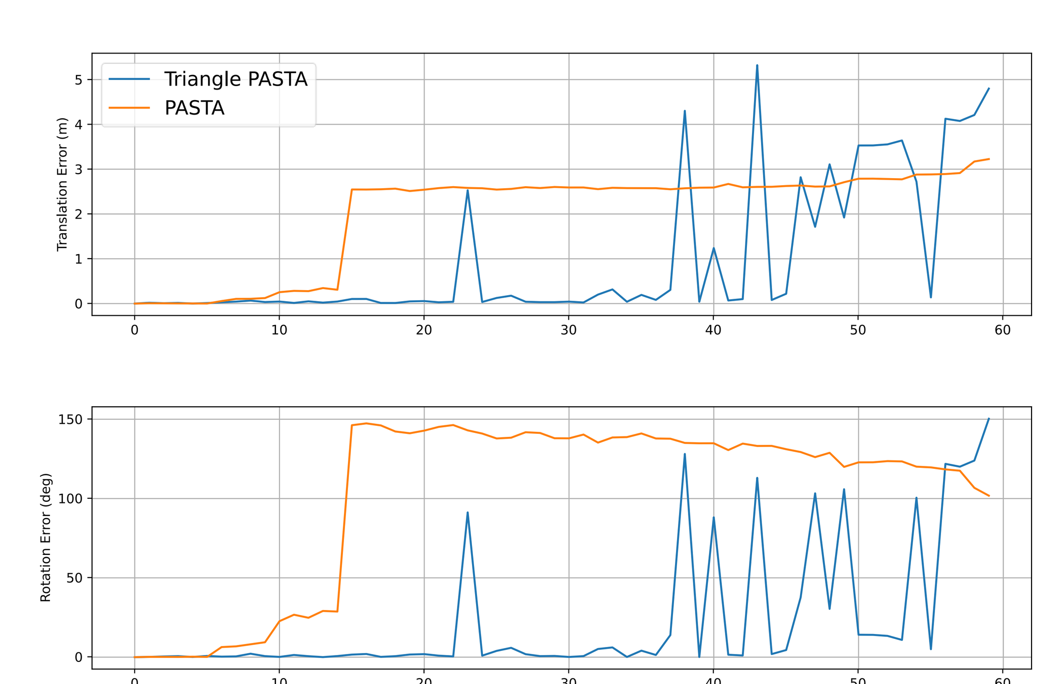
Triangle PASTA Performance

- We compare Triangle PASTA's performance against old PASTA.



- A robot moves in a non-convex environment so that its starting position is completely occluded at the end of its path while recording point clouds with a 2D LiDAR.

- We align each point cloud along the robot's trajectory with the initial point cloud.
- Triangle PASTA provides more accurate roto-translation estimates than old PASTA, especially as the overlap between point clouds shrinks.



Award ID#: 2211146

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