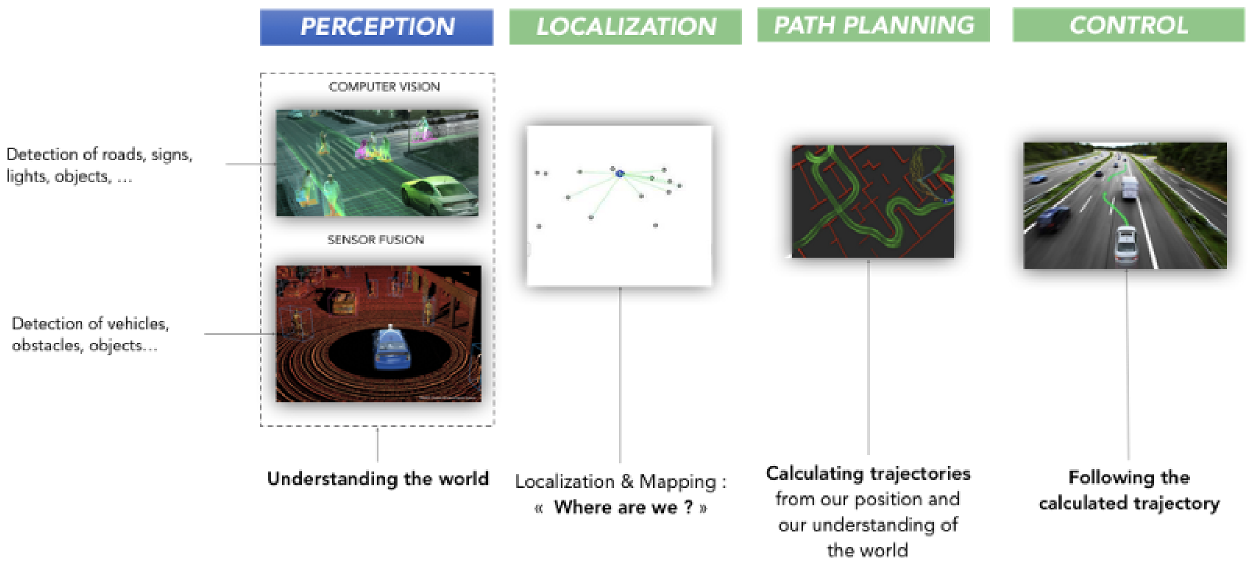
Survey

1. Introduction

Autonomous Driving can be broadly broken down into four parts:



- Perception: Use of sensors to understand the environment around the robot. Following are the sensors primarily used in autonomous systems:
  - *LIDAR:* Light Detection and Ranging or LIDAR measures distance to the surrounding object points using a laser and is the most preferred sensor for a robust autonomous system.
  - *Camera*: Very useful to understand the type of objects.
  - *Radar:* Used to detect speed of moving objects.
  - *Sonar:* Used as a redundant sensor to detect nearby objects for crash prevention.
- Localisation: It is the ability to localize a robot in a predefined local or global map. GPS can typically localise on a global map with about 5m accuracy but we will need to use other sensors like LIDAR (LIDAR based SLAM) or Camera (Visual SLAM) to localize the robot in a GPS denied environment or localise in a local map with higher precision.
- Path Planning: Once we know exactly where the vehicle is at any given instant and where the vehicle would like to go, we can create multiple optimal or suboptimal paths from source to destination using a variety of path planning algorithms. (similar to Google Maps)
- Control: After localising in a local environment and having an optimal path, we can use control to ensure that the vehicle stays on the optimal path.

2. SLAM (Simultaneous Localization And Mapping)

2.1 Mapping

Before the autonomous vehicle starts to navigate in an environment, it requires a map of the environment as prior knowledge. It can compare the map against its sensor data to localise itself. Building a map of the environment, comprising various features or landmarks is called mapping. To create a map of the environment, we can run a SLAM system that makes observations of the environment at different locations and then this data can be used to create a map. Or we could also collect data from various sensors manually and then build the map of the environment using offline processing.

Nowadays, there are a number of startups that are HD-mapping (map of the world upto centimetre accuracy) the world around us for self driving cars. These maps are usually represented as Feature maps, Grid maps, Topological maps or Point cloud maps that are further used by localisation algorithms. DEEPMAP, mapbox, Carmera, mapper, Civil Maps, propelmee, HERE and Tomtom are some of the popular ones out there.

2.2 Localisation

It is the process of localising the autonomous vehicle in an environment, based on the observations made by the vehicle and the map of the environment. This usually comprises of two steps:

- *Scene Recognition*: recognise the environment around us w.r.t. different points in the map.
- *Pose estimation*: or Coordinate Regression is next used to precisely regress the exact coordinates and heading of the robot.

It is noted that LIDAR based localisation techniques are better established than camera based because laser sensors are much more accurate and robust.

LIDAR based Localisation:

Cop et al.[1] used the intensity information from LIDAR along with descriptors to localise in an outdoor environment using LIDAR only. Wang et al.[2] propose a feature based weighted ICP for indoor localisation. Nicolai et al.[3] perform convolution on 3d voxels but don’t perform better than state of the art scan matching algorithms. Yin et al.[4] use Siamese based deep learning methods to learn representations and then apply registration based methods on the learned representations for localising poses estimates. Instead of using registration techniques, Barsan et al.[5] use deep learning for comparing between learned representations for performing localisation.

We can see very primitive use of deep learning based methods on the point clouds generated by lidar sensors which are not very competitive compared to traditional point-based methods and also not very robust to dynamic environments. Recent works by Caccia et al.[6] apply deep learning to accurately reconstruct the whole LIDAR scene which can then be used for downstream localisation tasks.

2.3 Online SLAM

An online SLAM system is a system that performs the task of building the map and localising itself in the same map typically in real time or soft real time. It is particularly used for exploring or building a map of an unknown environment but can also be used for localizing in a given map.

LIDAR based SLAM

There has been a very recent increased interest in applying deep learning to lidar data for online SLAM. On one hand, methods like Chen et al.'s[15], have used deep learning to improve geometric LIDAR based SLAM performance, whereas, on the other hand, methods like Chen et al.'s[16] use deep learning to robustly perform loop closures, one of the important subtasks in SLAM. In fact, Dinget al.'s[17] work is one of the latest works that apply end to end deep learning to perform offline SLAM.

Works by Hess et al.[7], Kohlbrecher et al.[8], Grisetti et al.[9] and Zhang et al.[10] are some of the popular methods for lidar based SLAM. A good number of LIDAR based SLAM survey works[11,12,13,14] have found Hess et al.'s[7], Cartographer to be the most robust and accurate LIDAR based SLAM compared to other methods available right now. Like other methods, Cartographer can also be manually tuned for different environmental and noisy conditions like number of dynamic objects.

Despite this, we have seen in our experiments that Hess et al's[7] Cartographer is still not quite robust in a dynamic environment, especially in an outdoor setting. Such problems can typically be handled by removing dynamic points[18]. Our experiments confirm that reconstructing to static LIDAR scene using deep learning can competitively improve the SLAM performance for any LIDAR based SLAM method. This can help us to use Cartographer for accurate mapping and localization in high dynamic environments like mining pits.

References

1. Cop, K.P., Borges, P.V. and Dubé, R., 2018, May. Delight: An efficient descriptor for global localisation using lidar intensities. In 2018 IEEE International Conference on Robotics and Automation (ICRA) (pp. 3653-3660). IEEE.
2. Wang, Y.T., Peng, C.C., Ravankar, A.A. and Ravankar, A., 2018. A single LiDAR-based feature fusion indoor localization algorithm. Sensors, 18(4), p.1294.
3. Nicolai, A., Skeele, R., Eriksen, C. and Hollinger, G.A., 2016, October. Deep learning for laser based odometry estimation. In RSS workshop Limits and Potentials of Deep Learning in Robotics (Vol. 184).

4. Yin, H., Tang, L., Ding, X., Wang, Y. and Xiong, R., 2018, June. LocNet: Global localization in 3D point clouds for mobile vehicles. In 2018 IEEE Intelligent Vehicles Symposium (IV) (pp. 728-733). IEEE.
5. Barsan, I.A., Wang, S., Pokrovsky, A. and Urtasun, R., 2018, October. Learning to Localize Using a LiDAR Intensity Map. In CoRL (pp. 605-616).
6. Caccia, L., Van Hoof, H., Courville, A. and Pineau, J., 2018. Deep generative modeling of LiDAR data. arXiv preprint arXiv:1812.01180.
7. Hess, W., Kohler, D., Rapp, H. and Andor, D., 2016, May. Real-time loop closure in 2D LIDAR SLAM. In 2016 IEEE International Conference on Robotics and Automation (ICRA) (pp. 1271-1278). IEEE.
8. Kohlbrecher, S., Von Stryk, O., Meyer, J. and Klingauf, U., 2011, November. A flexible and scalable slam system with full 3d motion estimation. In 2011 IEEE international symposium on safety, security, and rescue robotics (pp. 155-160). IEEE.
9. Grisetti, G., Stachniss, C. and Burgard, W., 2007. Improved techniques for grid mapping with rao-blackwellized particle filters. IEEE transactions on Robotics, 23(1), pp.34-46.
10. Zhang, J. and Singh, S., 2014, July. LOAM: Lidar Odometry and Mapping in Real-time. In Robotics: Science and Systems (Vol. 2, No. 9).
11. Filatov, A., Filatov, A., Krinkin, K., Chen, B. and Molodan, D., 2017, November. 2d slam quality evaluation methods. In 2017 21st Conference of Open Innovations Association (FRUCT) (pp. 120-126). IEEE.
12. Le, X.S., Fabresse, L., Bouraqadi, N. and Lozenguez, G., 2018, August. Evaluation of out-of-the-box ros 2d slams for autonomous exploration of unknown indoor environments. In International Conference on Intelligent Robotics and Applications (pp. 283-296). Springer, Cham.
13. Krinkin, K., Filatov, A., yom Filatov, A., Huletski, A. and Kartashov, D., 2018, May. Evaluation of modern laser based indoor slam algorithms. In 2018 22nd Conference of Open Innovations Association (FRUCT) (pp. 101-106). IEEE.
14. Coroiu, T. and Hinton, O., 2017. A Platform for Indoor Localisation, Mapping, and Data Collection using an Autonomous Vehicle. Master's Theses in Mathematical Sciences.
15. Chen, X., Milioto, A., Palazzolo, E., Giguère, P., Behley, J. and Stachniss, C., 2019, November. Suma++: Efficient lidar-based semantic slam. In 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 4530-4537). IEEE.
16. Chen, X., Läbe, T., Milioto, A., Röhling, T., Vysotska, O., Haag, A., Behley, J., Stachniss, C. and Fraunhofer, F.K.I.E., 2020. OverlapNet: Loop Closing for LiDAR-based SLAM. In Proc. of Robotics: Science and Systems (RSS).
17. Ding, L. and Feng, C., 2019. DeepMapping: Unsupervised map estimation from multiple point clouds. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 8650-8659).
18. Ruchti, P. and Burgard, W., 2018, May. Mapping with Dynamic-Object Probabilities Calculated from Single 3D Range Scans. In 2018 IEEE International Conference on Robotics and Automation (ICRA) (pp. 6331-6336). IEEE.