MRPB 1.0: A Unified Benchmark for the Evaluation of Mobile Robot Local Planning Approaches

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Abstract—Local planning is one of the key technologies for mobile robots to achieve full autonomy and has been widely investigated. To evaluate mobile robot local planning approaches in a unified and comprehensive way, a mobile robot local planning benchmark called MRPB 1.0 is newly proposed in this paper. The benchmark facilitates both motion planning researchers who want to compare the performance of a new local planner relative to many other state-of-the-art approaches as well as end users in the mobile robotics industry who want to select a local planner that performs best on some problems of interest. We elaborate design various simulation scenarios to challenge the applicability of local planners, including large-scale, partially unknown, and dynamic complex environments. Furthermore, three types of principled evaluation metrics are carefully designed to quantitatively evaluate the performance of local planners, wherein the safety, efficiency, and smoothness of motions are comprehensively considered. We present the application of the proposed benchmark in two popular open-source local planners to show the practicality of the benchmark. In addition, some insights and guidelines about the design and selection of local planners are also provided. The benchmark website [1] contains all data of the designed simulation scenarios, detailed descriptions of these scenarios, and example code.

I. INTRODUCTION

Motion planning is one of the most popular research topics in mobile robotics and has been widely investigated [2]–[5]. For computational efficiency reasons, the commonly adopted motion planning framework is organized in a hierarchical architecture by combining a global planner and a local planner [6]. The global planner is employed to generate a global path from the current robot pose to the goal one, followed by the local planner supposed to provide safe, flexible, and efficient motions according to real-time sensor data. In such a two-level planning scheme, the global planner only provides rough motion guidance for the robot, while the local planner plays a leading role in generating actual motions. In this work, we focus on the problem of mobile robot local planning.

Despite mobile robot local planning approaches have been widely investigated, there is still a lack of a unified benchmark for performance evaluation. When a new local planner is proposed, the authors usually make some comparisons with other approaches through customized designed simulation or experimental scenarios. However, data sets of these designed scenarios are usually unavailable, which makes it difficult for other researchers to repeat the evaluation. Additionally, the authors may choose some specific scenarios that are friendly to their proposed approach. Therefore, it is difficult to guarantee the comprehensiveness and objectivity of the evaluation. In addition to the public data sets, there is also a lack of a complete and principled evaluation system for mobile robot local planning approaches. The use of quantitative metrics is usually limited to the total travel distance or the time taken by the robot to complete the navigation task. To make an objective performance comparison, it is necessary to use a combination of different evaluation metrics that qualify different aspects of local planners. In summary, there is a lack of public data sets for evaluating mobile robot local planning approaches, as well as principled and comprehensive evaluation metrics.

In this paper, a mobile robot local planning benchmark called MRPB 1.0 is newly proposed to evaluate mobile robot local planning approaches in a unified and comprehensive way. We aim to establish a complete and principled evaluation framework that allows for objectively comparing the performance of local planners. To fulfill the goal, various simulation scenarios are designed and three types of evaluation metrics are proposed.

1) Data Sets: In order to improve the comprehensiveness and repeatability of performance evaluation, various simulation scenarios are elaborately designed and open-source. We choose Gazebo [7] as the simulation platform since its high popularity among the open-source Robot Operating System (ROS) community. On this basis, we carefully design four types of simulation scenarios, namely indoor, narrow space, partially unknown, and dynamic.

a) The indoor scenarios including various-scale office-like environments are designed to make an overall evaluation of local planners.

b) The narrow space scenarios such as complex maze environments, narrow passages, U-shaped or Z-shaped corridors, and so on are designed to challenge the flexibility and smoothness of local planners.

c) The partially unknown scenarios, i.e., only incomplete prior information is available for local planners, are
The designed simulation scenarios and evaluation metrics are detailed in Sections III and IV respectively. Section V presents the application of the proposed benchmark and Section VI comes to a conclusion.

II. RELATED WORK

Public data sets and benchmarks play an important role for scientific evaluation and objective comparison of algorithms. Previous research on mobile robot navigation benchmarks mainly focused on simultaneous localization and mapping (SLAM) techniques, and in particular on evaluating the precision of pose estimation [10]–[12]. In [13], Sprunk et al. design an experimental protocol to evaluate the whole navigation system in real environments. The concept of a reference robot is introduced for comparison between different navigation systems in different experimental scenarios. In the work [14], an extensive infrastructure for analysis and visualization of sampling-based path planning algorithms is proposed and integrated into the well-known Open Motion Planning Library (OMPL) [15]. Compared with several successful benchmarks in the area of computer vision [16]–[18], there is relatively little research on motion planning benchmarks in robotics.

In this paper, we newly propose a mobile robot local planning benchmark called MRPB 1.0 to evaluate mobile robot local planning approaches in a unified and comprehensive way. A variety of simulation scenarios are elaborately designed, taking into account large-scale, partially unknown, and dynamic complex environments. Furthermore, three types of principled evaluation metrics are proposed to comprehensively evaluate the performance of local planners from different aspects. We present the application of the proposed benchmark in two popular open-source local planners to show the practicality of the benchmark. All data of the benchmark is available on our website [1].

III. DATA SETS

To comprehensively evaluate the performance of local planners, we carefully design four types of simulation scenarios. In this section, these simulation scenarios are detailed.

A. Indoor Scenarios

The indoor scenarios of various-scale office-like environments are designed to make an overall evaluation of local planners. The scenario shown in Fig. 1(a) is a 29.4 × 21.9 m² indoor office environment, and the scenario depicted in Fig. 1(b) is designed according to the floor plan of a 35.2 × 35.3 m² shopping mall. These two large-scale office-like environments are used to evaluate the applicability of local planners. In addition, two relatively small-scale family house-like scenarios are designed, as illustrated in Fig. 1(d).
and (e). These two scenarios are used to challenge the safety and flexibility of local planners in the environment with dense obstacles.

**B. Narrow Space Scenarios**

In order to pose more challenges on the performance of local planners, we carefully design several narrow space scenarios. The scenario shown in Fig. (c) is a \(23.7 \times 25.5m^2\) maze environment. This is an extremely challenging scenario. Firstly, the robot needs to turn continuously in the maze, requiring local planners to provide flexible motions. Secondly, the passage of the maze is relatively narrow, which requires safe motion commands to prevent the robot from colliding with the wall. In summary, the maze scenario poses a huge challenge to the flexibility and safety of local planners.

In addition to the large-scale maze scenario, we also design two relatively small-scale narrow space scenarios. As shown in Fig. (f), a scenario with continuous U-shaped turn is designed. The robot needs to turn continuously in the narrow passage. In Fig. (g), we design an acute-angle turning scenario. At the corner, the orientation of the robot needs to be changed by approximately \(135^\circ\). These scenarios are both designed to challenge the flexibility of local planners.

**C. Partially Unknown Scenarios**

In the previously designed scenarios, the complete prior map is input to local planners. To challenge the adaptability of local planners in partially unknown environments, we blur the map manually and input the incomplete map to local planners. As illustrated in Fig. (a), the occupancy grid map of the indoor office environment shown in Fig. (a) is constructed by combining laser scan data with ground truth. On this basis, we mark a rectangle of \(13.9 \times 8.3m^2\) in the center of the map and set the covered cells to the unknown state, as shown in Fig. (b). Then the local planning is performed in the partially unknown grid map. Local planners need to update the occupancy grid map according to real-time laser scan data and provide safe and efficient motion commands for the robot. In addition to the indoor office environment, we also design a similar scenario for the shopping mall environment.

**D. Dynamic Scenarios**

We design several dynamic scenarios to challenge the robustness of local planners in dealing with dynamic obstacles. As depicted in Fig. (a)-(b), we simulate two people in the shopping mall environment. These two people are walking around in the T-shaped corridor at a constant speed. The robot is required to implement fast re-planning in
the changing environment to avoid collisions with dynamic obstacles. We design a similar scenario for the indoor office environment. Furthermore, a more complex dynamic scenario with several moving people is designed to challenge local planners. As shown in Fig. 3(c), six people are walking around in an open space environment. The robot needs to pass through the crowd to reach the goal at the other end. This scenario highly reproduces the crowded scene in the real world and poses a great challenge to the safety, flexibility, and real-time performance of local planners.

IV. METRICS

A. Data Log

Suppose that in the process of robot navigation from the start pose to the goal one, the local planning is called \(n\) times. Every time the local planning is called, we need to log the following data: the timestamp of the \(i\)-th call \(t_i\), the robot pose \((x_i, y_i, \theta_i)\), the linear and angular velocities \((v_i, \omega_i)\), the distance to the closest obstacle \(d_i\), and the time consumption of the local planning \(c_i\). When the robot completes the navigation task, we obtain the intermediate data of the whole navigation process \(\{t_1, x_1, y_1, \theta_1, v_1, \omega_1, d_1, c_1\}, 1 \leq i \leq n\).

B. Safety Metrics

The safety metrics are employed to evaluate the security performance of local planners in guiding the robot to the goal. In this work, the minimum distance to the closest obstacle \(d_o\) and the percentage of time spent by the robot in the dangerous area around obstacles \(p_o\) are used to evaluate the security of local planners

\[
d_o = \min \{d_i\}, 1 \leq i \leq n, \quad (1)
\]

\[
p_o = \frac{\sum (t_b - t_a)}{t_n - t_1} \times 100\%, \quad (2)
\]

where the subscripts \(a\) and \(b\) are the indices of timestamps satisfying \(d_k \leq d_{safe}, a \leq k \leq b\), and \(d_{safe}\) is the preset safe distance to obstacles.

C. Efficiency Metrics

The efficiency metrics are used to evaluate the motion efficiency and computational efficiency of local planners. The motion efficiency measures how quickly the local planner guides the robot to the goal, and the computational efficiency evaluates the real-time performance of local planners. In this work, the total travel time \(T\) is used to evaluate the motion efficiency

\[
T = t_n - t_1. \quad (3)
\]

And the computational efficiency is measured by the average time consumption of a single local planning

\[
C = \frac{1}{n} \sum_{i=1}^{n} c_i. \quad (4)
\]

D. Smoothness Metrics

The smoothness metrics are employed to evaluate the quality of motion commands provided by local planners. In this work, the smoothness performance of local planners is comprehensively evaluated by the path smoothness and velocity smoothness. We broadly follow the smoothness constraint defined in [19] to evaluate the path smoothness

\[
f_{ps} = \sum_{i=2}^{n-1} \left\| \Delta x_{i+1} - \Delta x_i \right\|^2, \quad (5)
\]

where \(\Delta x_i = x_i - x_{i-1}, 2 \leq i \leq n\) denotes the displacement vector at the vertex \(x_i = (x_i, y_i)^T\). And the velocity smoothness is measured by the average of the acceleration

\[
f_{vs} = \frac{1}{n-1} \sum_{i=1}^{n-1} \left| \frac{v_{i+1} - v_i}{t_{i+1} - t_i} \right|. \quad (6)
\]

V. APPLICATION

A. Setup

As mentioned before, we choose Gazebo as the simulation platform since its high popularity among the ROS community. Currently, the benchmark is released with ROS Kinetic and Gazebo 9. All the evaluations are performed on a laptop with an Intel Core i5-7200U processor and 8 GB RAM.

In the evaluation, we focus on the local planning problem of differential drive mobile robots. We refer to the popular Pioneer 3-DX mobile robot and design a robot model in Gazebo through the XML macros language Xacro. The footprint of the robot is broadly set to a circle with a radius of 0.17m. On this basis, a laser rangefinder is mounted on the robot. The laser rangefinder has an angular range of 180° with an angular resolution being 0.25°, and the maximum measurement range is set to 30m.
To make a fair comparison between different local planners, some common parameters such as the maximum and minimum linear velocities should be set to the same. The settings of these parameters are enumerated in Table I wherein $\bar{v}, \bar{\omega}, \bar{a}$, and $\bar{\alpha}$ denote the linear velocity, angular velocity, linear acceleration, and angular acceleration respectively. The period of the local planning thread is set to 0.2s, and the safe distance to obstacles is set to 0.34 m, i.e., twice the radius of the robot. Considering the computational efficiency, the local planning is performed in a 5.5 × 5.5 m$^2$ local map with the resolution being 0.1 m/cell. In addition, the robot pose is obtained from the ground truth provided by Gazebo to avoid the influence of localization error. To roughly describe the distance traveled by the robot during the navigation process, we also present the path length in the evaluation results. The two local planners of DWA and TEB each have some specific parameters to be set. Except for the common parameters enumerated in Table I, we use their own default parameters for the evaluation.

### B. Evaluation

To reduce the randomness of evaluation, we select multiple sets of different start and goal poses to test local planners in each scenario except for the scenario depicted in Fig. [1](g), since this is a one-way environment. Tables II, III, and IV enumerate the quantitative statistics of local planning results in the static, partially unknown, and dynamic scenarios respectively. Scenarios (a)-(g) correspond to the scenarios shown in Fig. [1](a) and Scenario (h) corresponds to the dynamic scenario depicted in Fig. [3](c). We use “N/A” to indicate the result of failure. It should be emphasized that the computation efficiency is related to the performance of the computing platform.

#### 1) Comparison on Efficiency

According to the evaluation results, it is concluded that TEB achieves superior performance than DWA in computational efficiency and motion efficiency. DWA needs to forward simulate and evaluate each pair of sampled velocities and does not take into account the environmental information during sampling. Therefore,
### TABLE III
**Quantitative Statistics of Local Planning Results in Partially Unknown Environments**

| Scenario (a) | Safety | Efficiency | Smoothness | Path length |
|-------------|--------|------------|------------|-------------|
| DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB |
| 1 | 1 | 0.22 | 0.32 | 4.9 | 1.2 | 37.5 | 34.0 | 42.9 | 3.9 | 0.25 | 0.02 | 0.06 | 0.02 | 18.58 | 18.57 |
| 2 | 2 | 0.22 | 0.25 | 3.6 | 3.5 | 61.2 | 57.0 | 42.9 | 3.2 | 1.38 | 0.02 | 0.05 | 0.02 | 30.70 | 30.87 |
| 3 | 3 | 0.20 | 0.28 | 15.5 | 2.9 | 44.5 | 41.8 | 44.7 | 3.9 | 0.54 | 0.02 | 0.10 | 0.02 | 22.86 | 22.96 |
| 4 | 4 | 0.22 | 0.30 | 10.1 | 1.3 | 53.7 | 46.6 | 41.6 | 4.1 | 0.18 | 0.04 | 0.16 | 0.05 | 25.61 | 24.25 |
| 5 | 5 | 0.20 | 0.27 | 4.3 | 4.2 | 65.5 | 59.4 | 40.5 | 4.8 | 0.92 | 0.03 | 0.09 | 0.02 | 30.99 | 30.83 |
| Scenario (b) | Safety | Efficiency | Smoothness | Path length |
| DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB |
| 1 | 1 | 0.32 | 0.28 | 0.0 | 1.4 | 49.9 | 43.4 | 39.8 | 3.2 | 3.79 | 0.02 | 0.07 | 0.03 | 23.55 | 23.58 |
| 2 | 2 | 0.28 | 0.29 | 1.5 | 0.9 | 97.2 | 76.7 | 41.7 | 4.3 | 3.10 | 0.05 | 0.10 | 0.03 | 40.32 | 36.02 |
| 3 | 3 | 0.28 | 0.32 | 0.0 | 0.7 | 75.9 | 59.8 | 39.9 | 4.0 | 4.46 | 0.02 | 0.05 | 0.02 | 32.81 | 32.27 |
| 4 | 4 | 0.32 | 0.28 | 0.1 | 2.8 | 113.0 | 105.4 | 42.0 | 4.6 | 7.34 | 0.05 | 0.04 | 0.02 | 58.18 | 57.84 |
| 5 | 5 | 0.20 | 0.25 | 2.5 | 2.6 | 65.0 | 61.9 | 39.4 | 3.8 | 0.86 | 0.04 | 0.09 | 0.05 | 31.72 | 32.34 |

### TABLE IV
**Quantitative Statistics of Local Planning Results in Dynamic Environments**

| Scenario (a) | Safety | Efficiency | Smoothness | Path length |
|-------------|--------|------------|------------|-------------|
| DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB |
| 1 | 1 | 0.22 | 0.32 | 3.7 | 0.7 | 31.4 | 29.2 | 37.0 | 5.5 | 0.26 | 0.02 | 0.08 | 0.03 | 15.69 | 15.85 |
| 2 | 2 | 0.14 | 0.32 | 7.0 | 1.3 | 34.3 | 29.8 | 28.8 | 4.7 | 0.17 | 0.02 | 0.13 | 0.05 | 15.03 | 15.16 |
| 3 | 3 | 0.28 | 0.34 | 7.2 | 0.0 | 32.5 | 30.2 | 32.7 | 4.8 | 0.29 | 0.02 | 0.09 | 0.02 | 16.15 | 16.14 |
| 4 | 4 | 0.22 | 0.20 | 8.5 | 6.0 | 32.3 | 36.6 | 32.1 | 5.6 | 0.23 | 0.07 | 0.11 | 0.08 | 15.78 | 18.37 |
| 5 | 5 | 0.22 | 0.30 | 3.2 | 1.1 | 40.1 | 37.2 | 36.5 | 5.1 | 0.18 | 0.01 | 0.07 | 0.02 | 20.41 | 20.48 |
| Scenario (b) | Safety | Efficiency | Smoothness | Path length |
| DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB | DWA | TEB |
| 1 | 1 | 0.32 | 0.18 | 0.3 | 15.3 | 46.8 | 61.6 | 31.2 | 6.2 | 0.20 | 0.11 | 0.05 | 0.11 | 23.50 | 28.52 |
| 2 | 2 | 0.20 | 0.32 | 5.7 | 0.9 | 36.8 | 44.8 | 32.9 | 4.9 | 1.73 | 0.01 | 0.06 | 0.03 | 25.14 | 24.56 |
| 3 | 3 | 0.28 | 0.29 | 0.7 | 0.6 | 63.1 | 61.0 | 34.1 | 5.3 | 3.14 | 0.02 | 0.05 | 0.02 | 33.28 | 33.50 |
| 4 | 4 | 0.41 | 0.32 | 0.0 | 0.0 | 59.9 | 56.6 | 35.7 | 4.9 | 2.82 | 0.01 | 0.06 | 0.03 | 30.39 | 30.69 |
| 5 | 5 | 0.28 | 0.32 | 0.7 | 0.6 | 76.9 | 66.2 | 37.7 | 5.4 | 1.84 | 0.02 | 0.05 | 0.02 | 37.86 | 35.61 |

2) Comparison on Safety: TEB employs a set of configurations to form a virtual band. The trajectory optimization is performed by applying artificial forces to the band, wherein the repulsive force stretches the band to avoid collision with obstacles. Therefore, the optimized path usually has a certain distance to obstacles. As shown in Tables III and IV, TEB achieves better security performance in most cases. Because of the better clearance from obstacles, the total travel distance of TEB is relatively longer than that of DWA.

3) Comparison on Flexibility: The evaluation results indicate that TEB performs better flexibility than DWA. Especially in scenarios like mazes that require robots to turn continuously, the shortcomings of DWA are obvious. As mentioned before, DWA performs forward simulation by applying each pair of sampled velocities for some short time. When the robot navigates in a narrow space, it is possible that considerable time is wasted in generating infeasible trajectories. While TEB takes the global path as the initial guess and obtains the local optimized trajectory through several iterations. As a result, planning with TEB is 8.94 times faster than planning with DWA. Furthermore, time optimality is explicitly considered in the optimization objectives of TEB. Therefore, TEB provides more efficient motion commands for the robot. Compared with DWA, the motion efficiency of TEB is increased by 9.2% on average.

In summary, the optimization-based local planner TEB performs better than the sampling-based local planner DWA in terms of efficiency, safety, and flexibility. For indoor navigation, such optimization-based local planners can provide more robust and reliable motion guidance for mobile robots, which may be a better choice for end users.

### VI. Conclusion
In this paper, we newly propose a mobile robot local planning benchmark called MRPB 1.0 to evaluate mobile robot local planning approaches in a unified and comprehensive.
way. Various simulation scenarios are elaborately designed and three types of principled evaluation metrics are proposed. We present the application of the proposed benchmark in two local planners to show the practicality of the benchmark.

REFERENCES

[1] https://github.com/NKU-MobFly-Robotics/local-planning-benchmark

[2] X. Zhang, J. Wang, Y. Fang, and J. Yuan, “Multilevel humanlike motion planning for mobile robots in complex indoor environments,” *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 3, pp. 1244–1258, 2019.

[3] W. Chi, C. Wang, J. Wang, and M. Q.-H. Meng, “Risk-DTRRT-based optimal motion planning algorithm for mobile robots,” *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 3, pp. 1271–1288, 2019.

[4] J. Wang, W. Chi, C. Li, C. Wang, and M. Q.-H. Meng, “Neural RRT*: Learning-based optimal path planning,” *IEEE Transactions on Automation Science and Engineering*, vol. 17, no. 4, pp. 1748–1758, 2020.

[5] J. Wang, M. Q.-H. Meng, and O. Khatib, “EB-RRT: Optimal motion planning for mobile robots,” *IEEE Transactions on Automation Science and Engineering*, vol. 17, no. 4, pp. 2063–2073, 2020.

[6] J. J. M. Lunenburg, S. A. M. Coenen, G. J. L. Naus, M. J. G. van de Molengraft, and M. Steinbuch, “Motion planning for mobile robots: A method for the selection of a combination of motion-planning algorithms,” *IEEE Robotics and Automation Magazine*, vol. 23, no. 4, pp. 107–117, 2016.

[7] N. Koenig and A. Howard, “Design and use paradigms for Gazebo, an open-source multi-robot simulator,” *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2004, pp. 2149–2154.

[8] D. Fox, W. Burgard, and S. Thrun, “The dynamic window approach to collision avoidance,” *IEEE Robotics and Automation Magazine*, vol. 4, no. 1, pp. 23–33, 1997.

[9] C. Rösmann, F. Hoffmann, and T. Bertram, “Integrated online trajectory planning and optimization in distinctive topologies,” *Robotics and Autonomous Systems*, vol. 88, pp. 142–153, 2017.

[10] W. Burgard et al., “A comparison of SLAM algorithms based on a graph of relations,” *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009, pp. 2089–2095.

[11] R. Künnmerle, B. Steder, C. Dornhege, M. Ruhnke, G. Grisetti, C. Stachniss, and A. Kleiner, “On measuring the accuracy of SLAM algorithms,” *Autonomous Robots*, vol. 27, pp. 387–407, 2009.

[12] F. Endres, J. Hess, N. Engelhard, J. Sturm, D. Cremers, and W. Burgard, “An evaluation of the RGB-D SLAM system,” *IEEE International Conference on Robotics and Automation*, 2012, pp. 1691–1696.

[13] C. Sprunk, J. Röwekämper, G. Parent, L. Spinello, G. D. Tipaldi, W. Burgard, and M. Jalobeanu, “An experimental protocol for benchmarking robotic indoor navigation,” *International Symposium on Experimental Robotics*, 2016, pp. 487–504.

[14] M. Moll, I. A. Sucan, and L. E. Kavraki, “Benchmarking motion planning algorithms: An extensible infrastructure for analysis and visualization,” *IEEE Robotics and Automation Magazine*, vol. 22, no. 3, pp. 96–102, 2015.

[15] I. A. Sucan, M. Moll, and L. E. Kavraki, “The open motion planning library,” *IEEE Robotics and Automation Magazine*, vol. 19, no. 4, pp. 72–82, 2012.

[16] A. Geiger, P. Lenz, and R. Urtasun, “Are we ready for autonomous driving? The KITTI vision benchmark suite,” *IEEE Conference on Computer Vision and Pattern Recognition*, 2012, pp. 3354–3361.

[17] J. Sturm, N. Engelhard, F. Endres, W. Burgard, and D. Cremers, “A benchmark for the evaluation of RGB-D SLAM systems,” *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012, pp. 573–580.

[18] S. Baker, D. Scharstein, J. P. Lewis, S. Roth, M. J. Black, and R. Szeliski, “A database and evaluation methodology for optical flow,” *International Journal of Computer Vision*, vol. 92, no. 1, pp. 1–31, 2011.

[19] D. Dolgov and S. Thrun, “Autonomous driving in semi-structured environments: Mapping and planning,” *IEEE International Conference on Robotics and Automation*, 2009, pp. 3407–3414.

[20] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, “Playing atari with deep reinforcement learning,” 2013, arXiv:1312.5602.