Study of Track Segmentation for Lap Time Optimization

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Abstract: Lap time minimization is of interest in every automotive racing competition. However, finding an optimal racing line is not a trivial task. In this work, we study one particular part of the racing line optimization problem, namely the track segmentation problem. We analyze how different track segmentation methods influence the racing line quality. Further, we present *Automated Segmentation based on Curvature* (ASC) method, which creates segments adaptively according to the track layout. Using lap time estimation based on a vehicle model, we compare ASC with two other methods from the literature. The preliminary results show that optimization based on ASC is able to outperform the other tested approaches by up to 15 % for the given number of iterations while converging to a good solution 3.88 times faster than the second-best method.

1 INTRODUCTION

The optimal racing line problem is of a common interest in an automotive racing environment (Caleffi et al., 2023). Its goal is to find a trajectory between two points, ensuring a minimum driving time when followed. On a closed circuit, this time is referred to as *lap time*.

Lap time minimization is one of the main goals of the *International F1/10 Autonomous Racing Competition* (https://f1tenth.org/), a racing event for student teams gathered from all around the world, utilizing 1:10 scaled-down car models, so-called *F1/10 cars* (Agnihotri et al., 2020).

Many techniques exist to find an optimal racing line, e.g., Evolution Strategies (O'Kelly et al., 2020), Genetic Algorithms (Klapálek et al., 2021), Model Predictive Control (Heilmeier et al., 2020; Cataffo et al., 2022), or one of the various machine learning methods (Evans et al., 2024). In (Braghin et al., 2008), authors use a genetic algorithm to minimize the following two criterions: (i) the path length so the distance the car has to drive is the shortest (i.e., shortest path), or (ii) the path curvature so that the maximum speed allowed by the surface friction is maximized (i.e., minimum curvature path).

Some of the above techniques rely on representing the racing track as a small number of disjoint track segments, where each of them represents a unit of optimization, thereby reducing the computational complexity. The *track segmentation* can be applied as follows. Each segment is associated with a single waypoint. The racing line is represented efficiently as an interpolation of a sequence of waypoints. Position of the waypoints within the segments is typically found by various optimization techniques (such as local search or genetic algorithms). Note that there exists a trade-off between the number of segments and the quality of the racing line. A large number of segments increase the solution space but slow the optimization convergence, whereas a low number of segments reduce the quality of the racing line or even make the problem unsolvable.

Specifically, the track segmentation approach is used in the following works. Garlick and Bradley (Garlick and Bradley, 2022) use it for training a neural network to find a racing line. In (Braghin et al., 2008), the authors have segmented the track equidistantly (meaning that the length of a segment along the centerline is constant), whereas, in the work of (Botta et al., 2012), the size of the segments was inversely proportional to the curvature of the track. In both works, the racing line waypoints were placed on a line perpendicular to the centerline. We call this

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line a *cut* and two consecutive cuts define a segment in between. This way, each waypoint is defined by its position in the sequence of segments and a single scalar variable describing its position on the cut, as can be seen in Fig. 1.

The exact way of segmenting the track likely influences the quality of the resulting racing line. However, the previous works did not study their relation in great detail and instead used simple and straightforward approaches. In this work, we study the effect of the track segmentation on the resulting racing line, considering both the solution quality (lap time) and computational effort (convergence of the algorithm). Specifically, the contribution of this paper is as follows: (i) we propose a method called *Automated Segmentation based on the Curvature* (ASC in short), and (ii) we compare ASC to two other approaches proposed in (Braghin et al., 2008) and (Botta et al., 2012), respectively. We show that given the same number of segments, our method is able to converge faster and yields lower lap times.

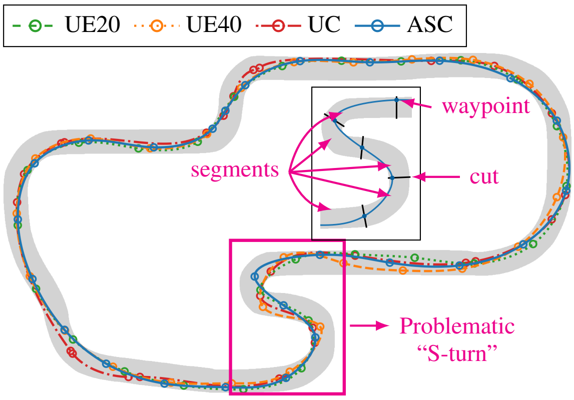


Figure 1: Ruudskogen map from TORCS (Wymann et al., 2014) with racing lines of selected methods and their waypoints, along with an illustration of segments, cuts, and waypoints.

2 METHODOLOGY

We compare three different methods for the track segmentation: (i) *uniform equidistant segmentation* (UE) based on (Braghin et al., 2008), (ii) *uniform segmentation with respect to the curvature* (UC) based on (Botta et al., 2012), and (iii) the *Automated Segmentation based on the Curvature* (ASC) method proposed in this work.

Considering the UE method, the quality of the racing line depends on the position of the initial segment. Thus, we evaluate multiple variants by moving the segments on the track along the centerline by $\alpha \cdot \Delta$, where $\alpha \in \{0\,\%, 10\,\%, \ldots, 90\,\%\}$ represents the shift and Δ is the length of the segment. We denote the method as UEα.

The UC method samples the cuts on the track uniformly with respect to the curvature, i.e. it places more cuts at the corners and less in the straight sections. However, to obtain a sufficient number of cuts in the straight sections, this method results in an unnecessarily high number of segments in the turns. We argue that the worse performance of the UC (in comparison to the UE-like approach as presented in (Botta et al., 2012)) was caused by a large number of segments in turns.

Similarly to UC, our ASC method places cuts based on track curvature. Contrary to the prior work, we generally divide the track into less segments. The ASC method works as follows: (i) positive and negative peaks on the curvature are found and populated by cuts, (ii) close cuts are merged to avoid redundancy, (iii) long cut-less sections of the track are artificially filled with equidistant cuts, (iv) sections of the track between two consecutive cuts where the sign of the curvature changes are populated with additional cuts, and (v) close cuts are filtered out once again. Therefore, the method segments the track automatically given the following parameters: threshold of curvature peaks, minimum distance between two cuts, and distance between cuts in the straight sections.

All the tested methods segment the track differently. To find the waypoints given the segmentation, we use a genetic algorithm powered by Nevergrad (Rapin and Teytaud, 2018). Note that the particular choice of the optimization technique is not that important, as any other optimization technique can be used instead. To get the racing line, we interpolate found waypoints by a cubic spline as presented in (Braghin et al., 2008). Finally, to evaluate the lap time t_{lap} given the racing line, we use a sequential two-step algorithm (Kapania et al., 2016). This algorithm computes a velocity profile using a dynamic bicycle model (with parameters suitable for an F1/10 car) to maximize the vehicle speed at any given point while not exceeding the maximum permissible vehicle speed (which depends on friction and the racing line curvature with a corresponding centripetal force) and acceleration limits.

We perform the experimental evaluation on the Ruudskogen map from TORCS (Wymann et al., 2014) shown in Fig. 1. The track is scaled by a factor of 1/10 to match the environment of the F1/10 competition. To ensure a fair comparison, the number of segments is fixed to 26. All of the tested methods (UE0, UE10, ..., UE90, UC, ASC) are executed three times, each time with a limit of 10,000 iterations (budget parameter of Nevergrad). The repeated evaluation is performed in order to mitigate the non-determinism of the optimizer.

3 RESULTS

The results of the experiments are shown in Fig. 2, illustrating the relation between the iteration number and best-so-far solutions found by the respective methods. Each data line represents the average of the three runs, with the filled area showing the standard deviation. Lap times achieved after 10,000 iterations are shown in the legend. Results for methods UE50, ..., UE90 are not presented since no feasible racing line was found in any of the runs. A racing line is infeasible if any part of it lies outside of the track. Note that the large standard deviation of the UC is caused by a large number of segments in the turns, which has a diverse impact on the optimizer convergence.

From Fig. 2 we conclude that ASC surpasses the best-performing variant of UE method (UE20) by 0.24 s (0.88 %) and UC by 3.49 s (11.47 %). Even though the difference between ASC and UE20 is not particularly high, note that UE20 is one of the possible rotations of UE method, while the success of individual rotations is a priori unknown.

The highest differences are most apparent in the early iterations. For example, after the first 500 iterations, using the ASC yields lap time that is 0.84 s (2.92 %) better than UE20, and 5.18 s (15.64 %) better than UC.

Figure 1 shows the racing lines for ASC, UE20, UE40, and UC methods. The most challenging part is the "S-turn" in the bottom part of the track, where cuts at inconvenient places negatively affects the lap time. Detailed view of the "S-turn" and how the selection of cuts influences a set of possible trajectories considered by the optimization algorithm is shown in Fig. 3. For example, we can see that the solution space of UE60 has only a small overlap with the track in the

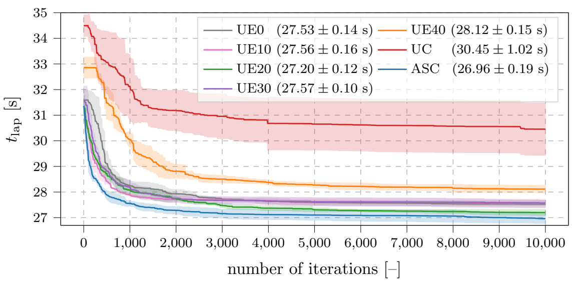
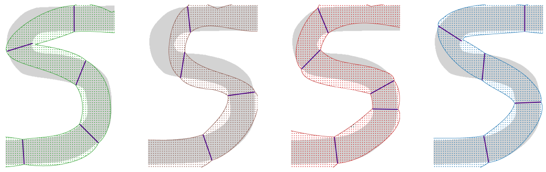


Figure 2: Comparison of tested methods, an average lap time is shown, along with the standard deviation represented as a filled area.

Table 1: Average number of iterations for given lap time.

t_{lap} [s]	ASC	UE0	UE10	UE20	UE30	UE40	UC
32.00	1	1	1	1	1	442	1,014
31.00	28	227	27	42	106	659	2,607
30.00	64	378	142	161	212	1,041	–
29.00	144	518	295	361	387	1,721	–
28.00	457	1,776	787	1,094	1,210	–	–
27.70	798	3,418	2,470	2,099	2,361	–	–
27.40	1,434	–	–	3,700	–	–	–
27.20	2,542	–	–	9,872	–	–	–
27.00	9,160	–	–	–	–	–	–



(a) UE20. (b) UE60. (c) UC. (d) ASC.

Figure 3: Cuts and solution spaces (dotted areas) of selected methods. The resulting racing line of each method has to lie in its solution space.

top part, which results in all potential solutions being infeasible. A racing line, which is feasible in the top left segment will be infeasible in the segment below it and vice versa.

Finally, Table 1 shows the average number of iterations needed to achieve certain lap times for the tested methods. Note that only ASC is able find to the best lap time under 27 s. In addition, ASC reaches the lap time of 27.2 s almost 4 times faster than UE20.

4 CONCLUSION AND FUTURE WORK

Lap time minimization is a common problem in racing competitions, and it strongly correlates with the quality of the racing line. In this paper, we studied the effects of track segmentation on racing line optimization. This preliminary study revealed the flaws of the previously used methods. Specifically, the *uniform equidistant segmentation* (UE) method may not adapt to the properties of the track, while the *uniform segmentation with respect to the curvature* (UC) method suffers from its dependency on the curvature smoothness.

We proposed the *Automated Segmentation based on the Curvature* (ASC) method overcoming these flaws and improving both the optimization convergence and the solution quality.

In the future, we plan to test ASC also on other tracks. Moreover, we plan to make the selection of various ASC parameters fully automatic and to validate it experimentally on a real F1/10 car. Besides, we want to test the effect of different interpolation functions (such as the Bézier curve). We believe that this study shows the high potential of adaptive track segmentation.

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REFERENCES

Agnihotri, A., O'Kelly, M., Mangharam, R., and Abbas, H. (2020). Teaching Autonomous Systems at 1/10th-scale: Design of the F1/10 Racecar, Simulators and Curriculum. In *Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, SIGCSE '20, pages 657–663, New York, NY, USA. Association for Computing Machinery.

Botta, M., Gautieri, V., Loiacono, D., and Lanzi, P. L. (2012). Evolving the optimal racing line in a high-end racing game. In *2012 IEEE Conference on Computational Intelligence and Games (CIG)*, pages 108–115. ISSN: 2325-4289.

Braghin, F., Cheli, F., Melzi, S., and Sabbioni, E. (2008). Race driver model. *Computers & Structures*, 86(13):1503–1516.

Caleffi, F., Rodrigues, L. d. S., Stamboroski, J. d. S., Rorig, B. V., Santos, M. M. C. d., Zuchetto, V., and Raguzzoni, Í. B. (2023). A systematic review of hardware technologies for small-scale self-driving cars. *Ciência e Natura*, 45(esp. 1):84071.

Cataffo, V., Silano, G., Iannelli, L., Puig, V., and Glielmo, L. (2022). A Nonlinear Model Predictive Control Strategy for Autonomous Racing of Scale Vehicles. In *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 100–105.

Evans, B. D., Trumpp, R., Caccamo, M., Jordaan, H. W., and Engelbrecht, H. A. (2024). Unifying f1tenth autonomous racing: Survey, methods and benchmarks. arXiv:2402.18558.

Garlick, S. and Bradley, A. (2022). Real-time optimal trajectory planning for autonomous vehicles and lap time simulation using machine learning. *Vehicle System Dynamics*, 60(12):4269–4289.

Heilmeier, A., Wischnewski, A., Hermansdorfer, L., Betz, J., Lienkamp, M., and Lohmann, B. (2020). Minimum curvature trajectory planning and control for an autonomous race car. *Vehicle System Dynamics*, 58(10):1497–1527.

Kapania, N. R., Subosits, J., and Christian Gerdes, J. (2016). A Sequential Two-Step Algorithm for Fast Generation of Vehicle Racing Trajectories. *Journal of Dynamic Systems, Measurement, and Control*, 138(9):091005.

Klapálek, J., Novák, A., Sojka, M., and Hanzálek, Z. (2021). Car racing line optimization with genetic algorithm using approximate homeomorphism. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 601–607.

O'Kelly, M., Zheng, H., Jain, A., Auckley, J., Luong, K., and Mangharam, R. (2020). Tunercar: A superoptimization toolchain for autonomous racing. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 5356–5362.

Rapin, J. and Teytaud, O. (2018). Nevergrad - A gradient-free optimization platform. https://GitHub.com/FacebookResearch/Nevergrad.

Wymann, B., Espié, E., Guionneau, C., Dimitrakakis, C., Coulom, R., and Sumner, A. (2014). TORCS, The Open Racing Car Simulator. http://www.torcs.org.