Decentralized Planning for Car-like Robotic Swarm in Unstructured Environments

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Abstract—Robot swarm is a hot spot in robotic research community. In this paper, we propose a decentralized framework for car-like robotic swarm which is capable of real-time planning in unstructured environments. In this system, path finding is guided by environmental topology information to avoid frequent topological change, and search-based speed planning is leveraged to escape from infeasible initial value’s local minima. Then spatial-temporal optimization is employed to generate a safe, smooth and dynamically feasible trajectory. During optimization, penalty is imposed on signed distance between agents to realize collision avoidance, and differential flatness cooperated with limitation on front steer angle satisfies the non-holonomic constraints. With trajectories broadcast to the wireless network, agents are able to check and prevent from potential collisions. We validate the robustness of our system in simulation and real-world experiments. Code will be released as open-source packages.

I. INTRODUCTION

Benefiting from the flexibility and stability, multi-robot systems can significantly accelerate task completion. Nowadays, car-like robotic swarms are widely applied in real life, such as autonomous trucks in ports and automatic guided vehicles in logistics warehouses. Most of these systems rely on centralized planning frameworks. However, with the robot quantity and map complexity increasing, centralized methods suffer from high computation burden, hence they lack the adaptability to dynamic environments, restricting the practical usage of car-like robotic swarms. For decentralized methods, limited by the performance of onboard processors, trajectory quality may not be guaranteed. To fill this gap, we propose a decentralized planning framework for car-like robotic swarm which is capable of real-time planning in unstructured environments.

Different from robots with holonomic kinematics such as quadrotors, car-like robots with non-holonomic and shape constraints bring more challenges for online planning in unstructured environments. During navigation, it is necessary to conduct frequent replans to avoid collisions with static and dynamic obstacles. Due to the non-holonomic kinematics, adjusting to rapid change in trajectories’ topological structure is more difficult for car-like robots, which results in a higher rate of colliding with static obstacles, especially when the distance between agent and obstacle is close, as shown in Fig.\textsuperscript{3}. To overcome this difficulty, we introduce topology-guided path planning to guarantee trajectory consistency, which means that the replanned path remains topology homotopy with the last planned one.

In the back-end optimization, initial values play an important role. Feasible initial values bring benefits such as speeding up optimization convergence and avoiding falling into bad solution’s local minima. Whereas infeasible initial time arrangement may lead to convergence to a solution where the trajectory is in collision with other agents. Having determined the spatial path from topology-guided path planning, in order to acquire reasonable initial time allocation, we introduce search-based speed planning, which realizes collision avoidance with other agents as well as dynamic feasibility.

Based on the spatial and temporal initial values, we employ a spatial-temporal joint optimization to generate a smooth, safe and feasible trajectory satisfying the non-holonomic constraints of car-like robots. The proposed system is an extension of our previous work [1], which lays a solid baseline for single car motion planning. In this system, a communication module is utilized to broadcast trajectories, based on which will other agents conduct real-time planning. The whole swarm system can traverse unknown environments while ensuring no collision between agents.

We validate the robustness of our system in a high-fidelity simulation platform for vehicles [2] and real-world
C. Topology-Guided Path Planning

Topological planning has been adopted in many scenarios to choose the best spatial path and avoid local minima. Jaillet et al. [12] construct visibility deformation roadmaps to define the topological homotopy and encode the environmental topological information. Zhou et al. [13], [14] extend visibility deformation to propose real-time planning by checking topological equivalence. Zhou et al. [15] construct distance fields in different directions of obstacles and utilize visibility deformation to find distinctive trajectories. In this paper, we extend visibility deformation in works [12], [13] to a broader definition to search for a path homeomorphic with the last planned path.

D. Speed Planning

Spatial-temporal decomposition is a widely used strategy in autonomous driving to improve planning efficiency, where speed planning is the temporal part. Works [16], [17] use search-based speed planning to search for a feasible speed profile. Works [18], [19] propose optimization-based speed planning methods to generate a smooth S-T (Space-Time) curve. Johnson et al. [20], [21] realize dynamic obstacle avoidance by propagating reachable velocity sets. Other works [22], [23] conduct speed planning by optimizing Bézier Polynomials. In this paper, we decouple space-time planning, where initial time span is provided by search-based speed planning. Then the initial path is refined by subsequent spatial-temporal optimization.

III. Path and Speed Planning

In this section, we will introduce topology-guided path planning and search-based speed planning, which will serve as spatial and temporal initial values for the back-end optimization.

A. Topology-Guided Path Planning

To generate a spatial reference path before optimization, we adopt the Kinodynamic hybrid A* [24] on the car case. Instead of sampling different poses, we directly sample different steering angles, and each motion primitive shares the same longitude distance. By limiting the maximum steering angle, the non-holonomic constraints can be satisfied initially.

The concept of topological homotopy has been analysed in [12], [13], which aims to capture candidate trajectories with different topological structures. However, both visibility deformation (VD) in [12] and uniform visibility deformation (UVD) in [13] require that candidate trajectories should share the same start and end point. In our searching process, replan start point may not be located on the previously searched path, hence we extend VD to a broader definition as SD-VD below:

**Definition 1:** For pre-defined distances $S, D \in \mathbb{R}^+$, two trajectories $\tau_1(s), \tau_2(s)$, parameterized by arc length $s \geq 0$, belong to the same SD-VD class if for all $s \leq S$, line $\tau_1(s)\tau_2(s)$ is collision-free, and $||\tau_1(s) - \tau_2(s)||_2 \leq D$. 

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1https://github.com/ZJU-FAST-Lab/Car-like-Robotic-swarm
B. Search-based Speed Planning

We introduce SD-VD into our path planning process to get a kinodynamic path homeomorphic with the last planned one. Before path searching, the previous kinodynamic path is stored as $r_0(s)$. When replan is triggered, each node point in $r_0(s)$ is iterated and the point $r_0(s_0)$ which is nearest to the replan start point is found out. The replan start point is noted as $r(0)$. Suppose the arc length of each motion primitive is $\Delta s$, and the position of the $k$-th primitive starting from the replan point is $r(k\Delta s)$. After that, find the corresponding primitive of the previous path $r_0(s_0 + k\Delta s)$, check if line $r(k\Delta s) - r_0(s_0 + k\Delta s)$ is collision-free and if $||r(k\Delta s) - r_0(s_0 + k\Delta s)||_2 \leq D$. If either of the above requirements is not satisfied, the newly searched primitive and the previous path is not in the same SD-VD class, and this primitive will not be accessed anymore. The SD-VD and searching process are shown in Fig.4. Distances $S$ and $T$ are chosen based on the sensing range and the robot’s kinematic properties, which demands that there is enough space for the robot to adjust the steering angle without colliding with obstacles. Subsequently, searched path lies in the same topological homotopy with the last planned path, guaranteeing trajectory consistency and avoiding collisions.

B. Search-based Speed Planning

Based on the spatial path generated in III-A and trajectories broadcast from other agents, an S-T graph is constructed before speed planning. As done in [17], we discrete arc length space $S$ and time space $T$, iterate points in S-T space and check if the ego robot is in collision with other agents. If colliding, the corresponding grid in the S-T graph is noted as a collision region, which means that this region is not accessible in speed planning.

Speed planning generates a time span satisfying dynamic obstacle avoidance and kinematic feasibility. We adopt search-based speed planning method, similar to [16], and conduct a 1-dimension $A^*$ search on the S-T graph. The control input is set as the tangential acceleration $A = \{a_{min} \leq a_1, \ldots, a_k \leq a_{max}\}$, and each child node shares the same time interval $T_f$. Starting from the initial state $x_0$, the forward expansion is:

$$
\begin{bmatrix}
  x_{i+1}^j \\
  \dot{x}_{i+1}^j
\end{bmatrix} = \begin{bmatrix}
  x_i + \dot{x}_iT_f + \frac{1}{2} a_jT_f^2 \\
  \dot{x}_i + a_jT_f
\end{bmatrix}, 1 \leq j \leq k. \tag{1}
$$

During the searching process, any node that violates the dynamic constraints or reaches the collision regions will be abandoned. The cost of each node is defined as:

$$J_p = J_g + \lambda_h J_h. \tag{2}$$

where $J_g$ means the time spent from the start state $x_0$ to the current state, $J_h$ represents the minimum time from the current state to the end state, and $\lambda_h$ is the weight parameter.

Note that the number of node states is growing rapidly during expansion, which suppresses the planner’s real-time performance. To solve this problem, we adopt two strategies.

1) **Node pruning mechanism:** In S-T graph construction, we discrete S space and T space. Based on that, we add velocity space discretization, thus each node state belongs to an S-T-V discretization grid. If the newly expanded node falls into the same S-T-V grid as one expanded node before, we only reserve the node with lower cost $J_p$, and the other is pruned, as shown in Fig.5. By restricting S-T-V space discretization, the amount of redundant node state can be significantly decreased.

2) **One-shot mechanism:** While accessing each expanded node, perform bang-bang control [25] directly from the current state to the end state. If bang-bang control curve on the S-T graph doesn’t intersect with the collision regions, the searching process is terminated and corresponding nodes serve as the final result of the speed planning. By applying one-shot mechanism, the searching process can finish in advance, which guarantees real-time performance.

IV. SPATIAL-TEMPORAL OPTIMIZATION

The content in this section is similar to our previous work [1]. For the integrity of this framework, we introduce the main mathematical deviations of optimization formulation, steer angle limitation and dynamic agent avoidance.

A. Trajectory and Optimization Formulation

We use differential flatness for the simplified kinematic bicycle model in the Cartesian coordinate to describe the four-wheel vehicle. As depicted in [26], states of car-like robots can be derived from the flat output $p := [p_x, p_y]^T$, 

![Fig. 4. This figure illustrates the topology-guided path planning. The purple curve is the newly replanned path in homotopy with the previously planned path. Whereas the green and brown dotted line is not in the SD-VD class with the blue line, therefore abandoned.](image)

![Fig. 5. Illustration of search-based speed planning on S-T graph. Red curves are the adopted nodes, and the green curve is the one-shot curve. The blue dotted lines are abandoned because of collision with obstacles or dynamical infeasibility. The red curve and the purple curve lie in the same S-T-V grid, and the purple node’s cost is higher, hence this node is pruned. Dynamic constraints or reaches the collision regions will be abandoned. The cost of each node is defined as: $J_p = J_g + \lambda_h J_h$.](image)
where $p$ means the position centered on rear wheel of the car.

Trajectory is formulated by a 2-dimensional polynomial with degree $N = 2m - 1$. In our framework we select $m = 3$. Suppose the segment of the trajectory consists of $M$ pieces, and pieces in a segment are time-uniform, where the time interval for each piece is $\delta T \in \mathbb{R}^+$, so the overall duration of the segment is $T = M \times \delta T$. For the $i$-th piece, the coefficient vector is $c_i \in \mathbb{R}^{2m \times 1}$, then this piece can be written as:

$$
p_i(t) := c_i^T \beta(t),
\beta(t) := \left[1, t, t^2, \ldots, t^N\right]^T,
$$

where $t \in [0, \delta T]$, and $i \in \{1, 2, \ldots, M\}$.

Before we introduce the optimization formulation, we first present the violation function $G_d$, where $d \in D$, and $D$ is the set of constraint terms such as dynamic feasibility, front steer angle limitation, static and dynamic obstacles collision avoidance. The mathematical description of the constraint terms is essentially inequality constraints:

$$
G_d \left(p_i(i), \ldots, p_{(m)}(i), \bar{t} \right) \leq 0,
$$

where $\bar{t}$ is the relative timestamp of some point in this piece, and $\bar{t}$ is the absolute timestamp of this point. Intuitively, $\bar{t}$ is to calculate the derivatives of the flat output $p$, but $\bar{t}$ is used to get the derivatives of the other robots’ flat outputs, which will be introduced in later subsection.

It is proved in [27] that the inequality constraints in Eq.(4) can be transformed into a penalty term $S_{\Sigma}$, and the formulation is an unconstrained nonlinear optimization problem:

$$
\min_{\c} J = \int_0^T \mu(t)^T \mu(t) dt + w_T T + S_{\Sigma}(\c, T),
$$

where $\c = [c_1, \ldots, c_M] \in \mathbb{R}^{2m \times M}$ is the coefficient matrix. $\mu(t)$ denotes the control efforts $p^{(m)}$, and $w_T$ represents the penalty weight on total time $T$.

Suppose each piece of a segment is discretized into $K \in \mathbb{N}^+$ constraint points to approximate the integral of the numerical penalty of each piece. The expression of the penalty term is:

$$
S_{\Sigma} = \sum_{d \in D} \sum_{i=1}^M \sum_{j=1}^K P_{d,i,j} (c_i, T),
$$

$$
P_{d,i,j} (c_i, T) = \frac{\delta T}{K} L_1 \left(G_{d,i,j}\right),
$$

where $w_d$ is the weight penalty, and $L_1(\cdot)$ is the L1-norm relaxation function. According to the chain rule, the gradients of $J$ w.r.t $c_i$ and $T$ are converted to the gradients of $G_d$ w.r.t $p, \bar{p}, \ldots, p^{(m)}$, $\bar{t}$ and $\bar{t}$. Next we will introduce the mathematical formulation of front steer constraints and obstacle avoidance.

### B. Front Steer Angle Limitation

The non-holonomic constraints of car-like robots mainly come from the front steer angle limitation. According to the differential flatness model, the steering angle $\phi$ can be expressed by the flat output:

$$\phi = \arctan \left(\frac{\eta (\dot{\bar{x}}_x \dot{\bar{y}}_y - \dot{\bar{y}}_x \dot{\bar{x}}_y)}{(\dot{\bar{x}}_x^2 + \dot{\bar{y}}_y^2)^{\frac{3}{2}}}\right),
$$

where $\eta \in \{-1, 1\}$, representing the car is moving forward or backward. $L$ is the wheelbase length. Then the curvature $C$ is:

$$C = \tan \frac{\phi}{L} = \frac{\dot{\bar{p}}^T \bar{H} \dot{p}}{\|\dot{p}\|_2^3},
$$

where $H := \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$. Suppose the maximum curvature is $C_m$, then the violation function is:

$$G_C(p, \bar{p}) = \frac{\dot{p}}{\|\dot{p}\|_2^3} - C_m.
$$

Then the gradients can be naturally derived as:

$$\frac{\partial G_C}{\partial \dot{p}} = \frac{H \dot{p}}{\|\dot{p}\|_2^3} - \frac{3}{2} \frac{\dot{p}^T \bar{H} \dot{p}}{\|\dot{p}\|_2^5} \dot{p},
$$

$$\frac{\partial G_C}{\partial \bar{p}} = \left[\frac{H \dot{p}}{\|\dot{p}\|_2^3} - \frac{3}{2} \frac{\dot{p}^T \bar{H} \dot{p}}{\|\dot{p}\|_2^5} \dot{p}\right]_1,
$$

$$\frac{\partial G_C}{\partial \bar{t}} = \frac{\partial G_C}{\partial \dot{p}} \frac{\partial \dot{p}}{\partial \bar{t}} + \frac{\partial G_C}{\partial \bar{t}} \frac{\partial \bar{t}}{\partial \bar{t}}.
$$

### C. Collision Avoidance

In our system, each agent is modeled as a convex polygon. In the optimization process, static obstacle avoidance is realized by constraining polygon in the convex safety corridors. Dynamical collision avoidance is satisfied by calculating the signed distances between convex polygons, and penalty is imposed if the distances are short.

Suppose $n_e$ and $n_o$ respectively represent the number of the vertexes of ego car and obstacle polygon, and the coordinates of the $e$-th and $o$-th vertex of ego car and obstacle car are $v_e^o$ and $v_o^e$, where $1 \leq e \leq n_e, 1 \leq o \leq n_o$. The index of the vertexes is counted clockwise. So the distance from the $o$-th vertex of the obstacle to the $e$-th edge of ego car is:

$$d_e^o = \frac{\|H(v_e^{o+1} - v_e^o)\|_2}{\|v_e^{o+1} - v_e^o\|_2}.
$$

For the $e$-th edge of ego car, iterate over all vertexes of obstacle and find the minimum distance:

$$d_{Ee} \approx \max_{e<0} \left(\left[d_1^e, \ldots, d_o^e, \ldots, d_{n_e}^e\right]^T\right).
$$

Then we choose the maximum value of $d_e$ as the signed distance from the obstacle to ego car:

$$d_{E}^o \approx \max_{e>0} \left(\left[d_1^e, \ldots, d_E^e, \ldots, d_{n_e}^e\right]^T\right).
$$

Likewise, the signed distance from the ego car to the obstacle is $d_{E}^o$. Note that a log-sum-exp function is leveraged to approximate and smooth the max and min functions. If $\alpha > 0$, the function returns the maximum value in the input vector,
and vice versa. Finally, the signed distance between ego car and obstacle is:

\[ d \approx \text{ls} e_{\alpha<0} \left( \begin{bmatrix} d^O e \ 0 \end{bmatrix}^T \right). \]  

(17)

The signed distance is shown in Fig.6.

Based on the signed distance above, the violation function of collision \( G_{EO} \) is defined as:

\[ G_{EO}(p, \dot{p}, t, \tilde{t}) = d_{tot} - d, \]

(18)

where \( d_{tot} \) is the safety margin distance. According to the chain rule:

\[ \frac{\partial G_{EO}}{\partial p} = -\text{ls} e'_{\alpha<0}(d^O e) \frac{\partial d^O e}{\partial p} - \text{ls} e'_{\alpha<0}(d^E e) \frac{\partial d^E e}{\partial p}. \]

(19)

\[ \frac{\partial d^E e}{\partial p} = \sum_{e=1}^{n} \text{ls} e'_{\alpha>0}(d_e) \left( \sum_{o=1}^{n} \text{ls} e'_{\alpha<0}(d^o e) \frac{\partial d^o e}{\partial p} \right), \]

(20)

Similarly, the gradient of \( G_{EO} \) w.r.t \( \dot{p}, \tilde{t} \) and \( \hat{t} \) are mainly about the gradient of \( d^E e \) and \( d^o e \) w.r.t \( \dot{p}, \tilde{t} \) and \( \hat{t} \). Suppose the \( e \)-th vertex of ego car’s relative coordinate to body frame is \( l^E e \), the rotation matrix is \( R \), and the vertex \( v^E e = p + Rl^E e \). Substitute \( v^E e, v^O e \) in Eq.(14) we can get:

\[ d^o e = \frac{[HR(l^E e + 1) - l^E e]^T}{||l^E e + 1 - l^E e||_2} (\dot{R}l^O e + \dot{p} - Rl^E e - p), \]

(21)

where \( \dot{R} \) and \( \dot{p} \) represent the rotation matrix and position of the obstacle, respectively. In this equation, \( R \) is associated with \( p, \dot{p} \) and \( \tilde{t} \), whereas \( \dot{R} \) and \( \dot{p} \) are associated with \( \hat{t} \). Therefore, the gradients of \( d^o e \) w.r.t \( p, \dot{p}, \tilde{t}, \hat{t} \) are further converted to the gradients of \( \dot{R}(p, \dot{p}, \tilde{t}) \) w.r.t \( p, \dot{p}, \tilde{t}, \hat{t} \), as well as the gradients of \( \dot{R}(\hat{t}) \) and \( \dot{p}(\hat{t}) \) w.r.t \( \hat{t} \).

Due to the page limitations, we will not present more mathematical derivations. For more details, we refer readers to our previous work [1].

V. SYSTEM ARCHITECTURE

The overall system architecture is shown in Fig.7. In this system, each agent is independent of each other, with trajectories broadcast by a wireless network. During navigation, each agent acquires point clouds and odometry information to construct 2-D grid maps. Then agents perform local planning based on the observed map and execute the trajectories by an MPC controller [28].

The communication network is utilized in this system to broadcast trajectories and to synchronize timestamps among agents. As depicted in Eq.(3), the information about trajectories only contains the coefficients and duration, which guarantees real-time communication. Therefore, the communication delay can be ignored in our system.

The point cloud is the direct message from sensors such as lidars, which provides high-precision information about the obstacles. Since our front-end planning algorithm is based on spatial-temporal decomposition, the point clouds of dynamic obstacles would highly hinder the spatial path planning process, especially when the robots are traversing obstacle-dense environments. To eliminate the point clouds of other agents, we make use of the broadcast trajectories, and calculate dynamic agents’ poses. Each agent is modeled as a convex polygon, and as a frame of point clouds is processed, each point is checked if it lies in the convex polygon. If so, the point is seen as the dynamic obstacle, and it is eliminated from the mapping process. By agent elimination, the remaining point clouds only come from static obstacles, freeing up enough space for path planning.

Benefiting from real-time performance, our system is capable of frequent replanning. The length of each replanned trajectory is less than the sensing range. While running, each agent conducts collision checks with static and dynamic obstacles. Replan is tackled as soon as a potential collision is detected, then a new trajectory is generated, simultaneously broadcast to other agents. In addition, replan is triggered if the agent has moved along half the length of the local trajectory, which aims to guarantee the motion coherence of the robot.

VI. EXPERIMENTS

We validate the robustness of our system in Carla [2] and real-world experiments. In this section, we first introduce simulation experiments and ablation studies. Then real-world experiments are presented.

A. Simulation Experiments

1) Environment Overview: Simulation experiments are conducted on a farm scene, where obstacles are closely arranged. The size of the scene is \( 90m \times 90m \), where 48 obstacles are randomly placed and there is no prior information about the environment, as shown in Fig. 6. We adopt Tesla Model 3 as the car model, where the maximum speed and acceleration are set as \( 8m/s \) and \( 3m/s^2 \), respectively. 3D lidar is utilized as the mapping sensor, and the maximum sensing range is \( 30m \), which also serves as the length of the
TABLE I. Time spent in planning

| Items     | $t_{pp}$ (ms) | $t_{sp}$ (ms) | $t_{cor}$ (ms) | $t_{opt}$ (ms) |
|-----------|---------------|---------------|---------------|---------------|
| Max       | 25.805        | 3.953         | 11.432        | 55.977        |
| Average   | 7.399         | 0.295         | 6.245         | 21.123        |
| Min       | 2.431         | 0.078         | 3.890         | 3.449         |

locally planned trajectory. CPU of the tested PC is Intel Core i7-10700, integrated with 16 GB RAM.

We simulate three cases: five cars driving from one side to the other, eight cars driving from two sides to the opposite sides, and eight cars driving from four sides to the opposite sides, respectively marked as case I, II, III, shown in Fig. 8. The average computation time is counted in Tab. I, where $t_{pp}$, $t_{sp}$, $t_{cor}$, and $t_{opt}$ respectively mean the time spent in path planning, speed planning, corridor generation, and spatial-temporal optimization. Average total time spent in planning is less than 40 ms and the maximum total time is less than 100 ms, exhibiting strong real-time performance.

2) Ablation Studies: To evaluate the necessity of topology-guided path planning and search-based speed planning, we conduct ablation studies in the three cases above. In each case varying the maximum velocity, we perform 10 trials, and the key metric is the number of successes that are collision-free. For the topology-guided path finding ablation, we eliminate the SD-VD class to cancel the trajectory consistency. For the search-based speed planning ablation, we directly adopt bang-bang control to provide an initial time arrangement. Results can be seen in Fig. 9, where TG and SP respectively represent Topological-Guidance and Speed-Planning. Without topological guidance or speed planning, the success rate falls off a cliff. Without topology-guided path planning, robot’s trajectories lose homotopy under frequent replans, and agents cannot decide which side to move, luring robots to collide with obstacles. Without speed planning, the initial values lead to a bad solution’s local minima, raising a higher rate of colliding with other agents. In conclusion, the adopted topology-guided path planning and search-based speed planning effectively increase the success rate.

B. Real-world Experiments

We conduct real-world experiments in $3m \times 8m$ environment, where three car-like robots move from one side to the other. Each robot is equipped with an NVIDIA Jetson Nano as the onboard processor and a laser scanner with 3 m sensing range, which is equal to the length of locally planned trajectories. Localization is done by a motion capture system. WI-FI is utilized to broadcast trajectories. The environment is unknown to the robots. Besides, mapping, planning and control are all performed onboard. Maximum speed and acceleration are set as $0.6 m/s$ and $1.0 m/s^2$, respectively. The experiments are shown in Fig. 10. Three agents manage to traverse the obstacle-rich environment, during which the obstacles are moved randomly, demonstrating robustness against the dynamic environment. For more information about the experiments, please watch our attached video.

VII. CONCLUSION

In this paper, a decentralized framework for car-like robotic swarm in unstructured environments is proposed. Topology-guided path planning and search-based speed planning are adopted to provide feasible initial values for the back-end optimization. Afterward, spatial-temporal optimization is employed to generate a safe and smooth trajectory. Experiments demonstrate its high efficiency in real-time planning and low collision risk. However, there still exist some problems resulting from the deadlock, which also accounts for the occasional collision in our experiments. In the future, we will try to solve these problems by introducing partial coordination and group planning. After that, this framework will be extended to 2.5D environments.
REFERENCES

[1] Z. Han, Y. Wu, T. Li, L. Zhang, L. Pei, L. Xu, C. Li, C. Ma, C. Xu, S. Shen, et al., “Differentiable flatness-based trajectory planning for autonomous vehicles,” arXiv preprint arXiv:2208.13160, 2022.

[2] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, “CARLA: An open urban driving simulator,” in Proceedings of the 1st Annual Conference on Robot Learning, 2017, pp. 1–16.

[3] Z. Zhu, E. Schmerling, and M. Pavone, “A convex optimization approach to smooth trajectories for motion planning with car-like robots,” in 2015 54th IEEE conference on decision and control (CDC). IEEE, 2015, pp. 835–842.

[4] J. Zhou, R. He, Y. Wang, S. Jiang, Z. Zhu, J. Hu, J. Miao, and Q. Luo, “Autonomous driving trajectory optimization with dual-loop iterative anchoring path smoothing and piecewise-jerk speed optimization,” IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 439–446, 2020.

[5] X. Zhang, A. Liniger, and F. Borrelli, “Optimization-based collision avoidance,” IEEE Transactions on Control Systems Technology, vol. 29, no. 3, pp. 972–983, 2020.

[6] B. Li, T. Acarman, Y. Zhang, Y. Ouyang, C. Yaman, Q. Kong, X. Zhong, and X. Peng, “Optimization-based trajectory planning for autonomous parking with irregularly placed obstacles: A lightweight iterative framework,” IEEE Transactions on Intelligent Transportation Systems, 2021.

[7] J. Alonso-Mora, P. Beardsley, and R. Siegwart, “Cooperative collision avoidance for nonholonomic robots,” IEEE Transactions on Robotics, vol. 34, no. 2, pp. 404–420, 2018.

[8] J. Alonso-Mora, A. Breitenmoser, P. Beardsley, and R. Siegwart, “Reciprocal collision avoidance for multiple car-like robots,” in 2012 IEEE International Conference on Robotics and Automation. IEEE, 2012, pp. 360–366.

[9] Y. Ouyang, B. Li, Y. Zhang, T. Acarman, Y. Guo, and T. Zhang, “Fast and optimal trajectory planning for multiple vehicles in a nonconvex and cluttered environment: Benchmarks, methodology, and experiments,” in 2022 International Conference on Robotics and Automation (ICRA), 2022, pp. 10746–10752.

[10] B. Li, Y. Ouyang, Y. Zhang, T. Acarman, Q. Kong, and Z. Shao, “Optimal cooperative maneuver planning for multiple nonholonomic robots in a tiny environment via adaptive-scaling constrained optimization,” IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 1511–1518, 2021.

[11] I. M. Delimpaltadakis, C. P. Bechlioulis, and K. J. Kyriakopoulos, “Decentralized platooning with obstacle avoidance for car-like vehicles with limited sensing,” IEEE Robotics and Automation Letters, vol. 3, no. 2, pp. 835–840, 2018.

[12] L. Jallet and T. Siméon, “Path deformation roadmaps: Compact graphs with useful cycles for motion planning,” The International Journal of Robotics Research, vol. 27, no. 11-12, pp. 1175–1188, 2008.

[13] B. Zhou, F. Gao, J. Pan, and S. Shen, “Robust real-time aav replanning using guided gradient-based optimization and topological paths,” in 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020, pp. 1208–1214.

[14] B. Zhou, J. Pan, F. Gao, and S. Shen, “Raptor: Robust and perception-aware trajectory replanning for quadrotor fast flight,” IEEE Transactions on Robotics, vol. 37, no. 6, pp. 1992–2009, 2021.

[15] X. Zhou, J. Zhu, H. Zhou, C. Xu, and F. Gao, “Ego-swarm: A fully autonomous and decentralized quadrotor swarm system in cluttered environments,” in 2021 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2021, pp. 4101–4107.

[16] J. Cheng, Y. Chen, Q. Zhang, L. Gan, C. Liu, and M. Liu, “Real-time trajectory planning for autonomous driving with gaussian process and incremental refinement,” in 2022 International Conference on Robotics and Automation (ICRA). IEEE, 2022, pp. 8999–9005.

[17] H. Fan, F. Zhu, C. Liu, L. Zhang, L. Zhuang, D. Li, W. Zha, J. Hu, H. Li, and Q. Kong, “Baidu apollo em motion planner,” arXiv preprint arXiv:1807.08048, 2018.

[18] C. Liu, W. Zhan, and M. Tomizuka, “Speed profile planning in dynamic environments via temporal optimization,” in 2017 IEEE Intelligent Vehicles Symposium (IV). IEEE, 2017, pp. 154–159.

[19] W. Xu and J. M. Dolan, “Speed planning in dynamic environments over a fixed path for autonomous vehicles,” in 2022 International Conference on Robotics and Automation (ICRA). IEEE, 2022, pp. 3321–3327.