


Moving Horizon Planning and Control for Autonomous Vehicles with Active Exploration and Fallback Strategies

Mohamed Soliman¹ and Rolf Findeisen² ^a

¹Laboratory for System Theory and Automatic Control, Otto-von-Guericke Universität Magdeburg, Germany

²Control and Cyber-physical Systems Laboratory, TU Darmstadt, Darmstadt, Germany

fi

Keywords: Active Exploration, Dual Control, Model Predictive Control, Obstacle Avoidance, Autonomous Vehicles.

Abstract: Navigating autonomous vehicles within a partially known environment to achieve a specific goal is an important yet challenging problem. It necessitates ensuring the safety of the vehicle along its trajectory, accounting for potentially unknown obstacles while maintaining the vehicle's ability to navigate the path at all times. Conventionally, a safe path is devised based on the available offline information. This does not exploit additional environmental information that can be obtained during movement. In a hierarchical moving horizon planning and control framework, we recast the lower-level vehicle control problem as a dual control problem, where the objective extends beyond merely following a given path, to include active exploration. This exploration involves acquiring additional information to reduce the uncertainty about obstacles encountered, potentially improving overall performance. Recognizing that active exploration can incur additional costs or lead the vehicle into situations where obstacles impede the traveled path, we propose a fallback strategy that involves returning to a known, possibly suboptimal, path. The approach is illustrated through simulations.


1 INTRODUCTION

The deployment of autonomous vehicles has a broad spectrum of applications, ranging from self-driving cars to unmanned aerial vehicles used, for example, in search and rescue missions (de Alcantara Andrade et al., 2019; Ibrahim et al., 2019; Nawaz et al., 2019). To perform their tasks, these systems include path planning and motion control components, which in all circumstances need to ensure collision avoidance and safety (Aggarwal and Kumar, 2020). Path planning and control are challenging in the presence of unknown or only partially known environments. Typically, planning is based on maps and complemented by onboard sensor data, such as camera systems or LIDAR. However, environmental information and maps are often incomplete due to limited sensing capabilities, such as range and field of view. This results in the challenge of control and planning under conditions of environmental uncertainty.

Missing environmental information often leads to conservative behavior to ensure obstacle avoidance under all conditions. This raises the question of whether planning and control can be

information/perception-aware to improve performance. In perception-aware planning, also denoted as information-aware re-planning, the objective is to derive a trajectory that facilitates exploration of the environment to acquire additional information regarding detected obstacles (Popović et al., 2024). Doing so potentially improves performance, enabling a more efficient trajectory. (Palazzolo and Stachniss, 2018) introduced an online exploration-aware algorithm that determines the next point to visit, where the expected information about the uncharted region is maximized. The work (Julian et al., 2014) strives to optimize a mutual information reward function to motivate the robot to explore new areas. Based on an information-theoretic framework, Folsom et al. (2021) employs rapidly exploring random tree algorithms for the Mars helicopter to collect information about the surface. The autonomous exploration of a mobile robot within an environment, delineated by an occupancy grid map, is described in (Wang et al., 2019).

From a control point of view, the challenge of active exploration is closely related to the concept of *dual control* (Mesbah, 2018; Feldbaum, 1960). Dual control considers that control actions impact information about the state of the system and vice versa.

^a  <https://orcid.org/0000-0002-9112-5946>

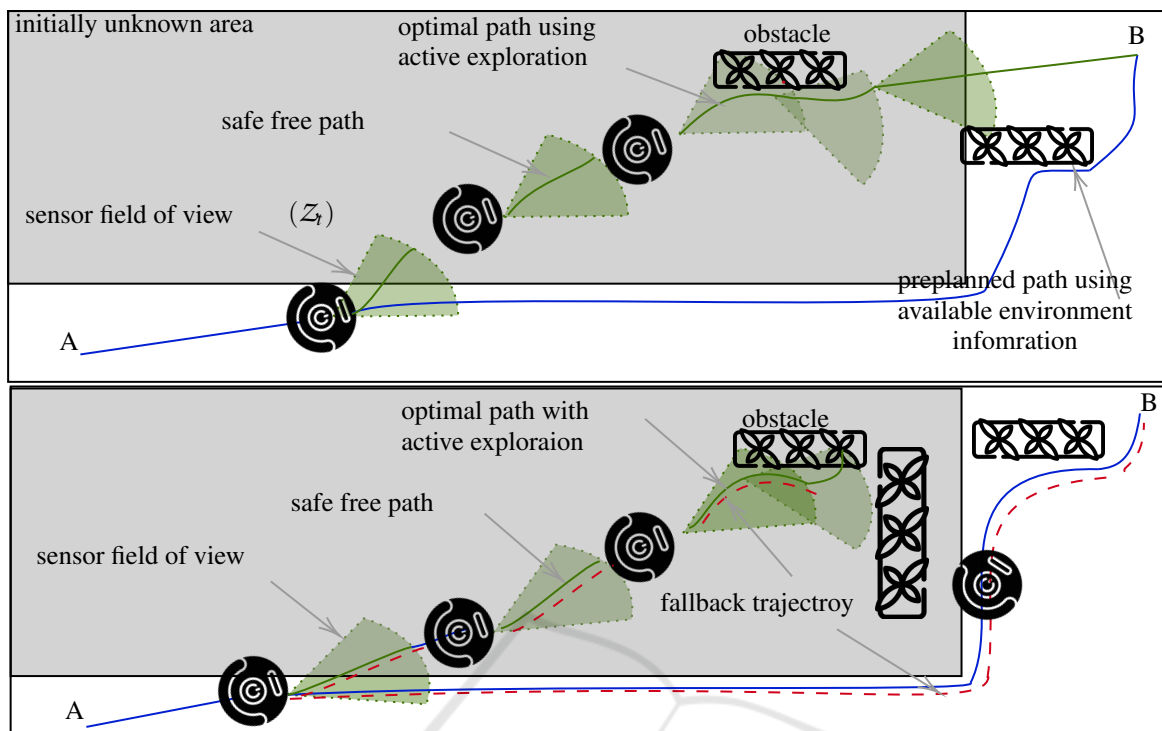


Figure 1: The figure above, the active exploration approach is activated that may lead to a shorter path to move from A to B: The vehicle starts along an offline planned safe path (solid blue line), that considers the unseen area depicted in grey as not safe, leading to a long but safe path to reach the goal B. Moving along the safe path the vehicle acquires additional environmental information in the sensors field of view Z_t , depicted as a green section in front of the vehicle. The active exploration is activated by augmenting the control, not the planning layer by an exploration term that allows departing from the preplanned path to explore and possibly find a shorter path to the goal, depicted by the solid green line. The figure below is the case where the fallback strategy is activated as the exploration steers the vehicle to a situation where it is obstructed by obstacles.

Achieving a balance between enhancing system information/environmental information and fulfilling the overarching control objective becomes important. Although exploration can potentially contribute to improving the overall objective, for example, if the autonomous vehicle reaches its destination in a shorter time, it is essential to recognize the potential increase in costs by prolonged exploration. In addition, there exists the risk that obstacles obstruct the movement of the autonomous vehicle. Therefore, it is crucial to integrate a fallback strategy designed to monitor exploration cost and environmental information gain and serve as an emergency mechanism, directing the autonomous vehicle along a safe path once the exploration becomes expensive or if obstacles obstruct the vehicle. A series of works have tackled the task of active exploration and control, and fallback options. In (Xue et al., 2018), an approach is introduced to address sensor failure, i.e. loss of environmental information, for unmanned vehicles, ensuring vehicle safety. (Genin et al., 2023) implemented a defensive fallback controller to improve the overall safety

of autonomous vehicles in cases where the primary controller misjudges the potential risk of pedestrian collisions. In (Sinha et al., 2023), a fallback safety controller is introduced to protect autonomous vehicles during a perception model failure, thus improving overall vehicle safety. (Soliman et al., 2022) introduced an active planning and control framework formulated as a dual optimal control problem to improve overall planning and control.

We consider autonomous ground vehicles equipped with onboard sensors with a limited sensor field of view, denoted Z_t , that is, the system has limited sensing capabilities; see Figure1.

We assume that an offline planned path is available based on the beforehand available environmental information. We outline a hierarchical moving horizon planning and control strategy, where the exploration is performed in the low-level vehicle controller, not the planning level. Although not performing a global perception-aware planning might limit the achievable performance, doing so simplifies computations and allows us to consider the information

gain during control from a dual-control perspective.

We propose that the autonomous vehicle follows the preplanned path passively; see Figure 1; without replanning or exploring until the sensors reach an unknown region or detect an obstacle. Upon detection of an obstacle, the lower-level controller explores the possible for a shorter way to reach the goal, while reducing the uncertainty about the obstacle. This is achieved by integrating an exploration objective into the moving horizon optimization task for control. If exploration becomes too expensive or the vehicle becomes stuck, a fallback mechanism is used, returning the autonomous vehicle to the safe path to reach the final destination; see Figure 1. The remainder of the paper is structured as follows. In Section 2, we present the problem formulation. Section 3 outlines the hierarchical planning and control scheme, including the lower-level exploration controller. Section 4 introduces the fallback strategy. The effectiveness of our approach is demonstrated in Section 5, before summarizing the findings in Section 6.

2 PROBLEM FORMULATION

We consider an autonomous vehicle equipped with onboard sensors that moves in a partially known environment with static obstacles; see Figure 1. The possibly nonlinear vehicle dynamics are given in discrete time:

$$x_{k+1} = f(x_k, u_k), \quad (1)$$

where $x \in \mathbb{R}^{n_x}$ and $u \in \mathbb{R}^{n_u}$ represent the vehicle states and control input, and $f: \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \rightarrow \mathbb{R}^{n_x}$. The state vector $x_k = [p_k^\top, \dots]^\top$ contains the center of mass coordinates $p_k \in \mathbb{R}^n$, orientation, and velocities, pitch, etc. The autonomous vehicle should move from an Initial position A to a Final position B. We assume that a safe path from A to B, based on the offline available environment avoiding unknown regions is available, see Figure 1.

2.1 Planning in the Sensor Field of View

We assume that the autonomous vehicle is equipped with an onboard sensor that has a limited field of view, Z_t see Figure 1. For simplicity, we assume that this field of view is shaped as an ellipsoidal segment, which is common for many sensor systems such as LIDAR, radar, and cameras. At each sampling time, t , the sensors onboard capture new information which is used for control or replanning of the path. Often, a hierarchical control and planning scheme is used, intertwining the planning and control problem. We

propose that, starting at point A, the preplanned safe path based on the offline map data is used by a model predictive path following controller (Matschek et al., 2019) to ensure the vehicle follows the path until the sensor's field of view, Z_t , encounters unknown regions or an unknown obstacle. At that point, a low-level exploratory controller is activated to explore the unknown region, potentially finding a more optimal path while considering the sensor field of view and the available map information, see Figure 2. Note that in principle, 'global' path planning could be performed whenever new environmental information is encountered to find a new optimal path. However, this approach is computationally expensive and often cannot be performed on the vehicle itself due to hardware limitations. Therefore, we propose online or sensor-based path planning when new information becomes available, with the aim of locally planning a safe path within the sensor's limited field of view. Upon detecting an obstacle O_i , where $i \in \{1, \dots, N_o\}$ and N_o is the number of obstacles, the local planner devises a safe path within the field of view.

Furthermore, note that we do not focus on uncertainties in the system dynamics or external disturbances acting on the vehicle. To ensure safety in these cases, one could perform an additional constraint backoff, that is, add a safety region around the obstacle (Soliman et al., 2022) and/or use tube-based predictive control techniques.

Performing path planning over the field of view is still generally computationally challenging for autonomous systems. Thus, we propose to use a hierarchical approach, where the low-level controller "hides" the systems' nonlinearities and uncertainties and performs the exploration, while the high-level planner uses a linear system model and is formulated as a mixed-integer optimization problem looking over a prediction horizon N_p covering the field of view Soliman et al. (2022). The mixed-integer formulation using the linear system model is formulated as:

$$\min_{\mathbf{u}^p, \mathbf{d}} \sum_{k=t}^{t+N_p} (\|p_k^p - p_B^p\|_\infty + \|u_k^p\|_\infty) \quad (2a)$$

$$\text{s. t.} \quad x_{k+1}^p = Ax_k^p + Bu_k^p, \quad x_t^p = \hat{x}(t), \quad (2b)$$

$$E_{i,t} p_k^p \geq e_{i,t} + M_{\text{big}}(\mathbf{1} - d_{i,k}), \quad (2c)$$

$$Z_t p_k^p \leq z_t, \quad (2d)$$

$$A_{\text{in}} x_k^p \leq b_{\text{in}}, \quad (2e)$$

$$\sum_{k=1}^{N_e} d_{i,k} = 1 \quad (2f)$$

Here, x_k^p denotes the predicted states of the linear model. $\hat{x}(t)$ is the measured system state at time t

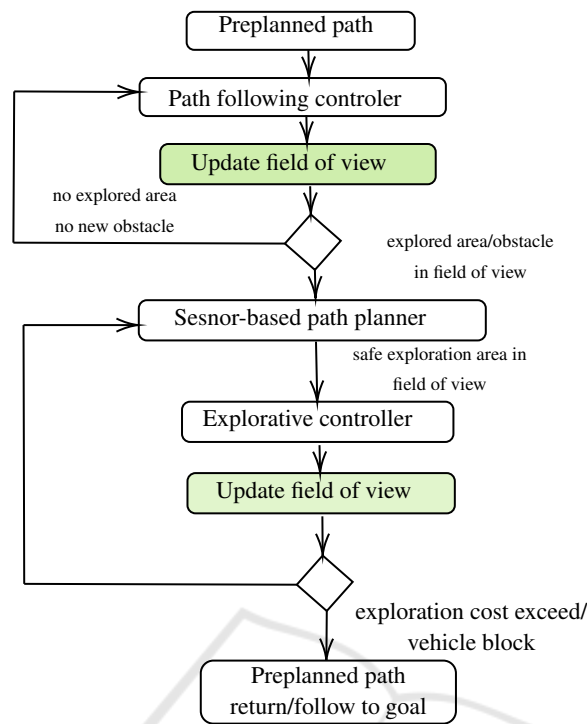


Figure 2: The global/offline planner plans a safe path based on the available environment information. The vehicle follows the preplanned path till unexplored area is detected by the onboard sensor field of view. The online/sensor-based planner plans a safe path within the current field of view and the dual explorative controller is active to explore the detected region/obstacle. When the vehicle is obstructed by other obstacles or the exploration cost is exceeded, the proposed fallback controller is activated to return the vehicle to the preplanned path till reach the goal.

and u_k^p are the system inputs. The safety of the vehicle is guaranteed by obstacle avoidance constraints (2c) with time-varying matrices of appropriate dimensions E , using the so-called big M formulation; see, e.g., (Williams, 2013). $e_{i,t}$ represents the detected obstacle i at time t . The predicted trajectory must be within the current field of view in (2d). In (2e) system constraints are considered. The binary variable constraint is considered in (2f). Solving (2) leads to an optimal reference $\mathbf{x}_t^* = [x_t^{p*T}, \dots, x_{t+N_p}^{p*T}]^T$ and a sequence of binary variables \mathbf{d}^* , related to the active obstacle constraints. Both are exploited in the low-level explorative controller. To incentivize the autonomous vehicle to explore the environment/obstacle, the detected obstacle is expressed by a virtual linear system subject to uncertainty. The initial condition of the virtual system \hat{w}_t is sent from the planner layer to the explorative controller. To obtain this information, first, all intersection points of Z_t , and the detected obstacle $G_{i,t}$ are determined, then the intersection point close to target B is selected; see Figure 3.

3 EXPLORATIVE LOW-LEVEL DUAL CONTROLLER

Encouraging the autonomous vehicle to collect information proactively about obstacles and explore its environment can improve control performance and overall objectives, such as reducing travel time to its destination (Soliman et al., 2022). Therefore, the low-level controller is tasked with incentivizing the autonomous vehicle to explore the environment in the safe field of view. To do so, a heuristic function is incorporated into the cost that encourages the controller to increase the information content or reduce the uncertainty, i.e., gain more information about the part of the obstacle behind the field of view. Specifically, the controller uses the reference trajectory \mathbf{x}_t^* , as well as a time-varying convex set \mathcal{L}_t that describes a convex obstacle-free region in the field of view; see Figure 3. If the vehicle model is perfect and the measurement uncertainty is negligible, the low-level controller can move freely within the set \mathcal{L}_t , as this avoids collisions. A possible safe convex set \mathcal{L}_t can be obtained from the

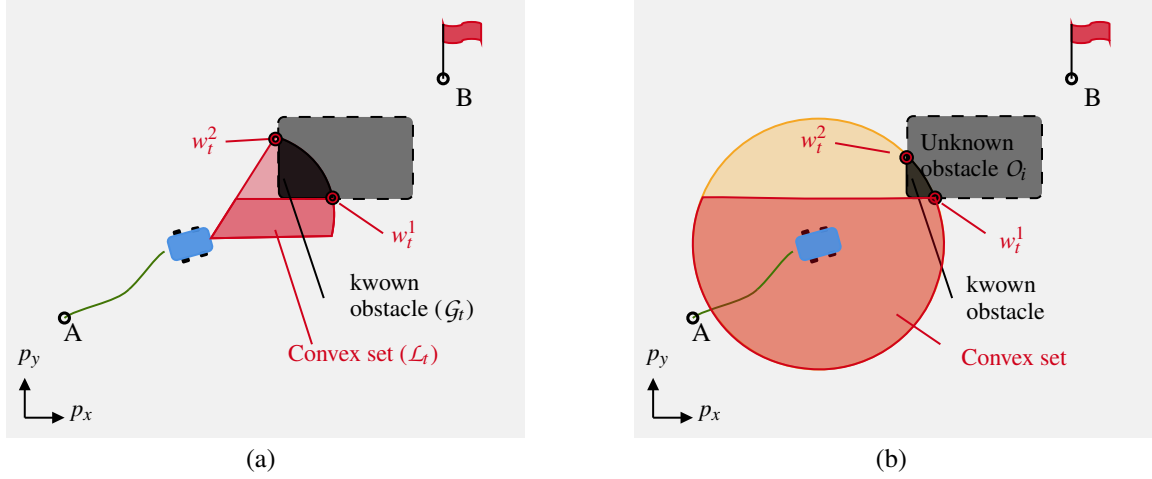


Figure 3: Two examples for the field of view and a convex subset of the safe convex set \mathcal{L}_t which is obstacle free. (a) shows the resulting set \mathcal{L}_t for a single obstacle in case of a field of view resulting from a camera sensor. (b) shows the resulting set \mathcal{L}_t for a single obstacle in case of a field of view resulting from a LIDAR sensor. Upon detection of obstacles, the intersection points between the field of view and the known obstacle \mathcal{G}_t are determined, and the point near the destination point B denoted w_t^1 or w_t^2 is sent to the controller. The safe convex set \mathcal{L}_t (in dark red) is the intersection between the current field of view and the binary variable d^* sent by the planner.

solution of (2) as:

$$\mathcal{L}_t := \begin{cases} p \in \mathbb{R}^3, \text{ such that} \\ E_{i,t}p \geq e_{i,t} + M_{\text{big}}(\mathbf{1} - d_{i,t}^*), \\ Z_t p \leq z_t, \\ \forall i \in [1, \dots, N_o]. \end{cases} \quad (3)$$

Since $d_{i,k}$ can change over time $k \in \{t, \dots, t + N_p\}$, there might exist several obstacles-free sets. Since the current position of the vehicle lies within the convex set, we take the convex set found at time t .

We are interested in improving the information, reducing the uncertainty, of the obstacle edge w_t close to the destination point B; see Figure 3, as this ‘represents’ the point where the uncertainty of the unseen obstacles ‘starts’. We will exploit this information in the low-level controller during the exploration task to decrease the uncertainty and gain more information about the obstacle. In our scenario, unseen parts of the obstacles are characterized by uncertainty, represented by the edges of the detected obstacle w_t that follow a virtual linear system influenced by Gaussian noise such that:

$$w_{k+1} = A^w w_k + B^w v_k, \quad v_k \sim \mathcal{N}(0, Q_k). \quad (4)$$

Here $w_{k+1} \in \mathbb{R}^3$ is the predicted obstacle edge with initial condition $w_t = \hat{w}_t$ received from the high-level planner. The uncertainty associated with the edge of the obstacle, is characterized by the covariance matrix Q_k . It is inherently related to vehicle dynamics and thus influences sensor information. The propagation

of \hat{w} is calculated using its mean and variance as:

$$\mu_k = \hat{w}_t, \quad (5a)$$

$$\sigma_{k+1} = g(\sigma_k, Q(x, u)). \quad (5b)$$

The function g in (5b) serves as a general estimator, capturing the influence of the predicted control signal on the propagation of uncertainty. It is important to note that we have assumed that the mean value of the dynamics of the obstacle remains constant at \hat{w}_t , while its uncertainty fluctuates with changes in the state of the system. The evolution of the autonomous vehicle states directly impacts the evolution of environmental uncertainty, denoted $Q(\cdot)$. The propagation function of environmental uncertainty can be expressed by uncertainty based on angle or distance; details can be found in (Soliman et al., 2022). Through the inclusion of an excitation term in the objective function, control signals facilitate not only control actions but also probing actions. Therefore, the overall dual optimal control problem in the low-level controller can be expressed as follows:

$$J(x_k, u_k, x_s, \sigma_k) := \sum_{k=t}^{k=t+N_p} W_1 F_1(x_k^c, u_k^c, x_k^{p,*}) + W_2 F_2(\sigma_k) + W_3 F_3(x_{t+N_p}^c, u_{t+N_p}^c). \quad (6)$$

Here F_1 penalizes the states with respect to the trajectory x_t^* given by planner, F_2 is an exploration function that can be expressed as the trace of the covariance matrix ($\text{tr}(\sigma_{k+1})$) and F_3 is a terminal penalty function. Furthermore, the weighting matrices W_1 and W_2

represent the trade-off between the control task objective and the exploration of the uncertainty learning objective, while W_3 is the terminal penalty weighting matrix.

Notably, the hierarchical controller optimally guides the autonomous vehicle, ensuring vehicle safety, while exploration is carried out within the safe convex set \mathcal{L}_t defined by the high-level planner. The resulting exploratory low-level controller is formulated on a moving horizon:

$$\min_{\mathbf{u}^c} J(x_k, u_k, x_s, \sigma_k) \quad (7a)$$

$$\text{s.t. } x_{k+1}^c = f(x_k^c, u_k^c), \quad x_t^c = \hat{x}(t), \quad (7b)$$

$$w_{k+1} \sim \mathcal{N}(\mu_k, \sigma_k), \quad (7c)$$

$$\sigma_{k+1} = g(\sigma_k, Q_k), \quad \sigma_k = \sigma_t, \quad (7d)$$

$$Q_k = e(\psi_k, \theta_t), \quad (7e)$$

$$\mu_k = \hat{w}_t, \quad (7f)$$

$$x_{k+1}^c \in \mathcal{L}_t, \quad u_k^c \in \mathcal{U} \quad (7g)$$

Here, $\mathbf{u}^c = \{u_t^c, \dots, u_{t+N_p}^c\}$ is the sequence of control actions. Only the first piece of the optimal control sequence is applied to the system, and the optimization is repeated. Equation (7b) represents the dynamics of the vehicle used in the low-level control layer using a nonlinear function $f: \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \rightarrow \mathbb{R}^{n_x}$. In particular, the predicted control trajectory affects the propagation of uncertainty through the constraints (7d) and (7e) where ψ represents the heading angle of the autonomous vehicle while θ_t represents the angle of the detected obstacle edge w.r.t. the fixed ground frame. In (7g), the system states lay in the safe convex set \mathcal{L}_t obtained from the planning. Furthermore, control signals u_k^c are limited to within the set \mathcal{U} , which can be chosen as a trade-off between the allowed level of aggressiveness and the smoothness of the trajectory (Berntorp et al., 2018).

Frequently, exploring increases the overall cost, mainly because the autonomous vehicle deviates from the optimal path. Therefore, there is a trade-off between strictly adhering to the safe trajectory provided by the high-level planner and engaging in exploration.

In scenarios where sensing capabilities are limited, e.g., a limited field of view and/or range, sensors may only provide partial information about obstacles. In such instances, the overall cost may become costly in comparison to the planned offline path available. Furthermore, the new path could be obstructed during exploration execution; see Figure 1. Therefore, we propose a fallback strategy that leads the vehicle back to the safe path to ensure the completion of the task, as outlined in the next section.

4 FALLBACK STRATEGY

If the cost for exploration becomes too high, or the system reaches a locked position, the fallback mode is activated; see Figure 2.

As a fallback strategy, we propose using an MPC trajectory tracking formulation that takes advantage of the off-line planned path and / or the safe route explored. To do so, the vehicle should be able to follow the path previously implemented. It is formulated as follows:

$$\min_u J_t(r^j(\cdot), u^j(k), x(k), u(k)) \quad (8a)$$

$$\text{s.t. } x_{k+1}^c = f(x_k^c, u_k^c), \quad x_t^c = \hat{x}(t), \quad (8b)$$

$$\Delta y_k = r^j(k) - h(x_{k+1}), \quad (8c)$$

$$\Delta u_k = u^j(k) - u_k, \quad (8d)$$

$$x_{k+1} \in \mathcal{X}, \quad u_k \in \mathcal{U}, \quad h(x_{k+1}) \in \mathcal{Y} \quad (8e)$$

Here, the path to follow enters via the output and input error dynamics (8c) and (8d). Furthermore, the reference $r^j(k)$ depends on time, that is, a new reference is available to the controller at each time step. This implies that the controller should drive the system to be in a specific state at specific times while respecting the state and control input constraints in and the nonlinear vehicle dynamics expressed in (8b) (Matschek et al., 2019). The reference trajectory can be designed prior to the execution of the autonomous vehicle motion and/or any additional waypoints explored by the vehicle during the exploration process facilitated by the dual controller. Note that the pre-planned path or trajectory incorporates both the offline path and the path explored in the exploration phase of the low-level controller.

5 CASE STUDY

We investigate a mobile robotic system that navigates a densely populated office environment. The robot has partial offline map information; see Figure 4; where regions without information are gray-shaded. Based on the map, an offline path planning algorithm leads to a safe path, incorporating obstacle data from the known areas, e.g., obstacles' positions and geometries, while circumventing the unexplored gray region. The robot has limited sensing capabilities, e.g., limited field of view and range. The mobile robot can be mathematically represented by a kine-

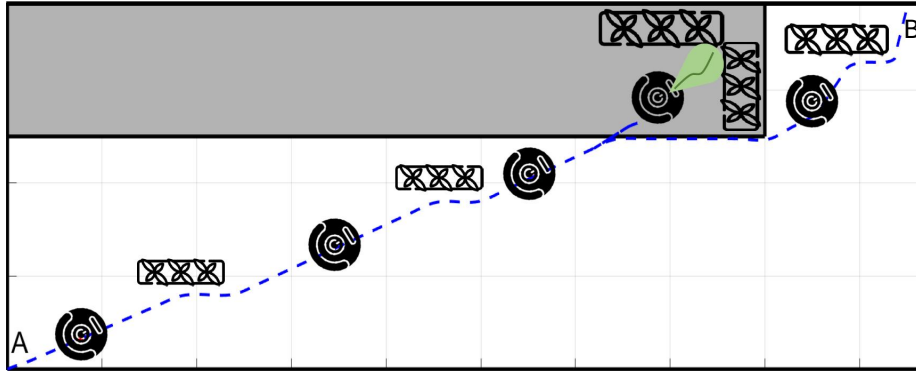


Figure 4: Employed planning and control strategy with low-level exploration controller if an unexplored area is encountered. The exploratory dual-control low-level controller is activated once the field of view enters the uncharted area. While the robot explores the area, it cannot find a shorter path as the robot is blocked by other obstacles. The fallback strategy is activated, leading the robot back to the safe path to reach the goal.

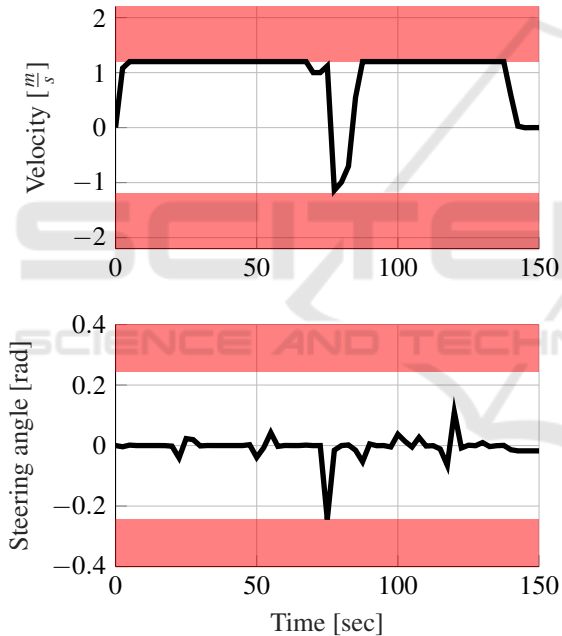


Figure 5: Resulting velocity and steering angle for the vehicle. Red areas represent the vehicle's mechanical constraints. The explorative low-level dual controller fully exploits the vehicle's capacity while respecting the autonomous vehicle's mechanical limitations.

matic bicycle model as follows (Jazar, 2017):

$$\dot{p}_x = v \cos(\psi). \quad (9a)$$

$$\dot{p}_y = v \sin(\psi). \quad (9b)$$

$$\dot{\psi} = v \tan(\delta) / L. \quad (9c)$$

$$\dot{v} = u_1. \quad (9d)$$

$$\dot{\delta} = u_2. \quad (9e)$$

Equations (9a) and (9b) represent the dynamics of the center of mass of the vehicle while the heading angle dynamics is given by (9c). The control inputs u_1 and u_2 are the acceleration and steering angle rates, respectively. As shown, the autonomous vehicle follows the preplanned offline path until the onboard sensor detects the presence of the gray region. Subsequently, an online path planning and control approach is adopted. Upon obstacle detection, an active exploration scheme is initiated, in which the vehicle accelerates to its maximum capabilities within the safe convex exploration set provided by the planner. Due to limited sensing capabilities, the autonomous vehicle could be obstructed by other obstacles or the exploration cost remains constant, indicating that no new information on the obstacle is acquired see Figures 4 and 6. The fallback trajectory tracking controller is then activated, utilizing the safe explored path and the preplanned path to guide the autonomous vehicle safely to the goal point while adhering to the vehicle's dynamic constraints (see Figure 5).

6 CONCLUSIONS

Navigating autonomous vehicles in partially or entirely unknown environments presents a significant challenge, requiring the controller to ensure the vehicle's safety while completing the designated task. Active exploration has been recognized as a method to enhance performance. We propose utilizing onboard sensor information within the vehicle's field of view to explore regions for which no information is available offline. To achieve this, we have integrated active exploration within a hierarchical moving hori-

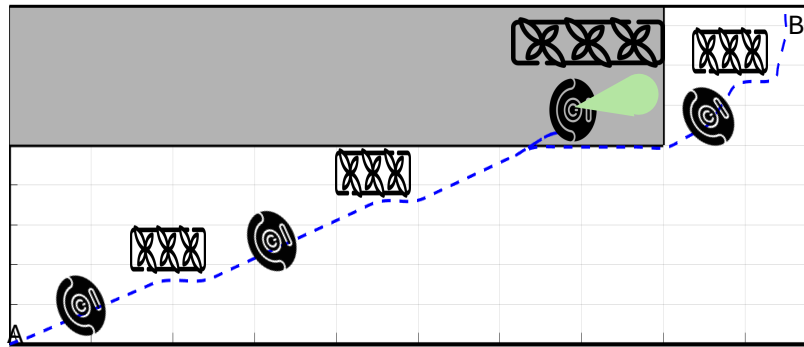


Figure 6: Employed planning and control strategy with low-level exploration controller if an unexplored area is encountered. The exploratory dual-control low-level controller is activated once the field of view enters the uncharted area. While the robot explores the area, the exploration costs increases as the robot cannot find a free path to the goal point. Fallback controller is activated leading the robot back to the safe path to reach the goal.

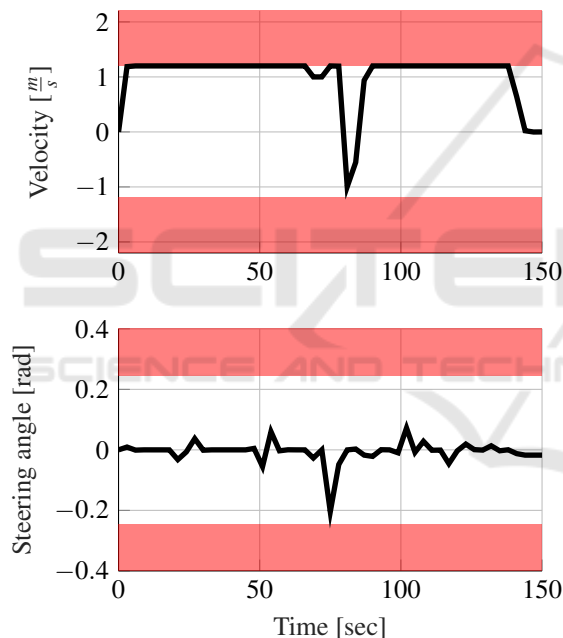


Figure 7: Resulting velocity and steering angle for the vehicle. Red areas represent the vehicle’s mechanical constraints. The explorative low-level dual controller fully exploits the vehicle’s capacity while respecting the autonomous vehicle’s mechanical limitations

zoning and control framework. For safe operation, active exploration is executed by the low-level controller, which can deviate from the preplanned path upon receiving new information from the onboard sensors about unknown areas. When obstacles are encountered, the additional information obtained through active exploration is used to reduce object uncertainties. We have also introduced a fallback strategy that activates if exploration becomes prohibitively

expensive or fails. Through simulation, we demonstrate the application of the proposed fallback controller to a mobile robot navigating a cluttered environment, with results highlighting its efficacy.

REFERENCES

Aggarwal, S. and Kumar, N. (2020). Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. *Computer Communications*, 149:270–299.

Berntorp, K., Hoang, T., Quirynen, R., and Di Cairano, S. (2018). Control architecture design for autonomous vehicles. In *2018 IEEE Conference on Control Technology and Applications (CCTA)*, pages 404–411. IEEE.

de Alcantara Andrade, F. A., Reinier Hovenburg, A., Netto de Lima, L., Dahlin Rodin, C., Johansen, T. A., Storvold, R., Moraes Correia, C. A., and Barreto Haddad, D. (2019). Autonomous unmanned aerial vehicles in search and rescue missions using real-time cooperative model predictive control. *Sensors*, 19(19):4067.

Feldbaum, A. A. (1960). Dual control theory. i. *Avtomatika i Telemekhanika*, 21(9):1240–1249.

Folsom, L., Ono, M., Otsu, K., and Park, H. (2021). Scalable information-theoretic path planning for a rover-helicopter team in uncertain environments. *International Journal of Advanced Robotic Systems*, 18(2):1729881421999587.

Genin, D., Dietrich, E., Kouskoulas, Y., Schmidt, A., Kobilarov, M., Katyal, K., Sefati, S., Mishra, S., and Papusha, I. (2023). A safety fallback controller for improved collision avoidance. In *2023 IEEE International Conference on Assured Autonomy (ICAA)*, pages 129–136.

Ibrahim, M., Matschek, J., Morabito, B., and Findelsen, R. (2019). Hierarchical model predictive con-

- trol for autonomous vehicle area coverage. *IFAC-PapersOnLine*, 52(12):79–84.
- Jazar, R. N. (2017). *Vehicle dynamics: theory and application*. Springer.
- Julian, B. J., Karaman, S., and Rus, D. (2014). On mutual information-based control of range sensing robots for mapping applications. *The International Journal of Robotics Research*, 33(10):1375–1392.
- Matschek, J., B athge, T., Faulwasser, T., and Findeisen, R. (2019). Nonlinear predictive control for trajectory tracking and path following: An introduction and perspective. In *Handbook of Model Predictive Control*, pages 169–198. Springer.
- Mesbah, A. (2018). Stochastic model predictive control with active uncertainty learning: A survey on dual control. *Annual Reviews in Control*, 45:107–117.
- Nawaz, H., Ali, H. M., and Massan, S. (2019). Applications of unmanned aerial vehicles: a review. *Tecnol. Glosas Innovaci n Apl. Pyme. Spec.*, (2019):85–105.
- Palazzolo, E. and Stachniss, C. (2018). Effective exploration for mavs based on the expected information gain. *Drones*, 2(1):9.
- Popovi c, M., Ott, J., R uckin, J., and Kochenderfer, M. J. (2024). Learning-based methods for adaptive informative path planning. *Robot. Auton. Syst.*
- Sinha, R., Schmerling, E., and Pavone, M. (2023). Closing the loop on runtime monitors with fallback-safe MPC. In *2023 62nd IEEE Conference on Decision and Control (CDC)*, pages 6533–6540.
- Soliman, M., Morabito, B., and Findeisen, R. (2022). Towards safe exploration for autonomous vehicles using dual model predictive control. *IFAC-PapersOnLine*, 55(27):387–392.
- Wang, C., Chi, W., Sun, Y., and Meng, M. Q.-H. (2019). Autonomous robotic exploration by incremental road map construction. *IEEE Transactions on Automation Science and Engineering*, 16(4):1720–1731.
- Williams, H. P. (2013). *Model building in mathematical programming*. John Wiley & Sons.
- Xue, W., Yang, B., Kaizuka, T., and Nakano, K. (2018). A fallback approach for an automated vehicle encountering sensor failure in monitoring environment. In *2018 IEEE Intelligent Vehicles Symposium (IV)*, pages 1807–1812.