Other Related Work

Summarizing drawbacks of the related work:

- Time and space complexity for physics based approach increases with the size of environment and the resolution of its representation.
- Search based approach i.e. A* will provide a solution but at a cost of time and memory. Reducing the resolution of the environment might cause unsafe paths. Modified/Improvised A* still doesn't solve this problem.
- General RRT's although fast in open spaces, tend to considerably slow down in narrow spaces. Several improvements in sampling solve this issue, but doesn't take into account the robot model and motions which is vital for obtaining a collision free path in confined spaces.
- The automotive approaches solely try to solve specific scenarios. Scaling the approach to a large environment will yield inefficient results. Also, dynamic environment cannot be handled.
- Motion predictive control although handles dynamic obstacles, cannot solve confined space navigation without optimal reference path.

Near Optimal Planning for Piano Mover's Problem

• **Requirements**: Map representing the environment, robot's dimensions, motion primitives (8-geometry maze router including rotation).

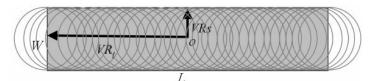


Figure 3: The rectangle model of a robot configuration.

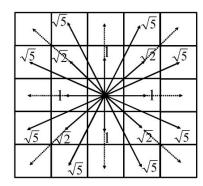


Figure 4: 8-geometry maze router.

1. Gene Eu Jan, Tong-Ying Juang, Jun-Da Huang, Chien-Min Su and Chih-Yung Cheng, "A fast path planning algorithm for piano mover's problem on raster," Proceedings, 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics., 2005, pp. 522-527, doi: 10.1109/AIM.2005.1511035.

Near Optimal Planning for Piano Mover's Problem

- **Requirements**: *Map representing the environment, robot's dimensions, motion primitives (8-geometry maze router including rotation).*
- Environment is decomposed into cells to a particular resolution and each cell carries seven set of information.
- O AT (Time of Arrival) uses the maze router to obtain cost from the start to current cell.
- Certain information are encoded before planning and the rest are assigned during planning.

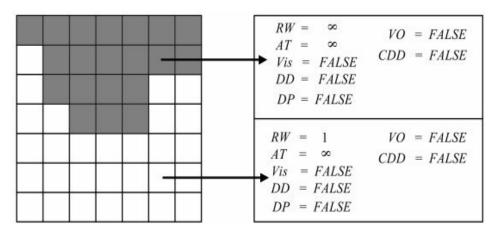


Figure 5: Cells data structures where RW (Regional Weight), AT (Time of Arrival), Vis (Visited), DD (Detection Diameter), DP (Detection Pie), VO (Virtual Obstacle), CDD (Collision-Detection Domain).

1. Gene Eu Jan, Tong-Ying Juang, Jun-Da Huang, Chien-Min Su and Chih-Yung Cheng, "A fast path planning algorithm for piano mover's problem on raster," Proceedings, 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics., 2005, pp. 522-527, doi: 10.1109/AIM.2005.1511035.

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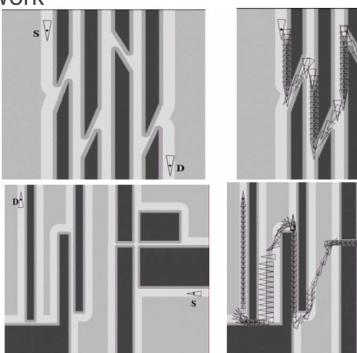


Figure 6: Illustration of the path planning of robot motion using rectangle model.

(b) the shortest path with

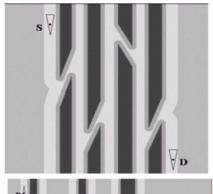
revisiting

(a) the initial configuration

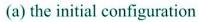
 Gene Eu Jan, Tong-Ying Juang, Jun-Da Huang, Chien-Min Su and Chih-Yung Cheng, "A fast path planning algorithm for piano mover's problem on raster," Proceedings, 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics., 2005, pp. 522-527, doi: 10.1109/AIM.2005.1511035.

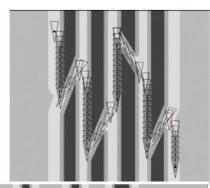
Near Optimal Planning for Piano Mover's Problem

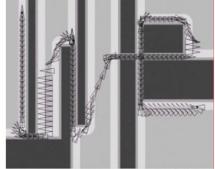
- **Requirements**: *Map representing the environment, robot's dimensions, motion primitives (8-geometry maze router including rotation).*
- Environment is decomposed into cells to a particular resolution and each cell carries seven set of information.
- AT (Time of Arrival) uses the maze router to obtain cost from the start to current cell
- Certain information are encoded before planning and the rest are assigned during planning.
- Path obtained by backtracking with the minimum value of time of arrival from the destination cell to the source cell taking into account the cost obtained by cell info.
- **Drawbacks**: Complexity increases as the resolution or size of the environment or number of motion primitives increase. Not suitable for long range navigation.











(b) the shortest path with revisiting

Figure 6: Illustration of the path planning of robot motion using rectangle model.

 Gene Eu Jan, Tong-Ying Juang, Jun-Da Huang, Chien-Min Su and Chih-Yung Cheng, "A fast path planning algorithm for piano mover's problem on raster," Proceedings, 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics., 2005, pp. 522-527, doi: 10.1109/AIM.2005.1511035.

Cylindrical Algebraic Decompositions (CAD)

- **Requirements**: *Map representing the environment, robot's dimensions.*
- The problem considers a moving ladder ([x, y], [w, z]) in configuration space.

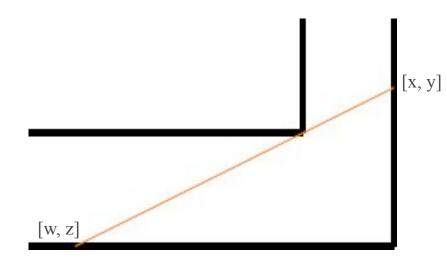


Figure 7: A configuration of a ladder in which the endpoints are in opposite branches of the corridor.

Cylindrical Algebraic Decompositions (CAD)

- **Requirements**: *Map representing the environment, robot's dimensions.*
- The problem considers a moving ladder ([x, y], [w, z]) in configuration space (representing tight corners).
- First, express all possible invalid regions, then take its negation,
 't' represents any point on the ladder.
- Quantifier Elimination by Partial CAD (QEPCAD) is used to construct cells and returning the equivalent quantifier-free expression.

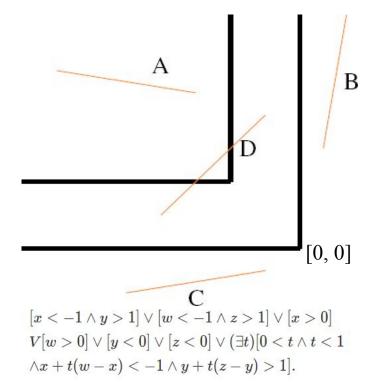


Figure 8: Four canonical invalid positions of the ladder and their expression.

Cylindrical Algebraic Decompositions (CAD)

- **Requirements**: Map representing the environment, robot's dimensions.
- The problem considers a moving ladder ([x, y], [w, z]) in configuration space (representing tight corners).
- First, express all possible invalid regions, then take its negation,
 't' represents any point on the ladder.
- Quantifier Elimination by Partial CAD (QEPCAD) is used to construct cells and returning the equivalent quantifier-free expression.
- Each cell is described by a semi-algebraic set (a finite sequence of polynomial equations and inequalities).

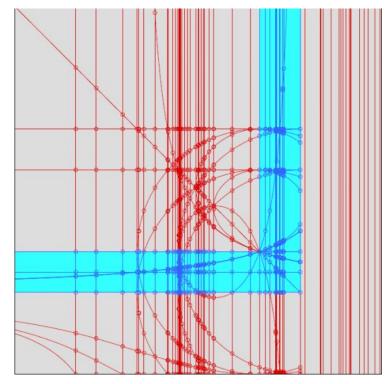


Figure 9: A two-dimensional CAD of just [x,y] point in configuration space.

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- **Requirements**: *Map representing the environment, robot's dimensions.*
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- First, express all possible invalid regions, then take its negation,
 't' represents any point on the ladder.
- Quantifier Elimination by Partial CAD (QEPCAD) is used to construct cells and returning the equivalent quantifier-free expression.
- Each cell is described by a semi-algebraic set (a finite sequence of polynomial equations and inequalities).
- O **Drawbacks**: Finding adjacency and connectedness of cells in the four-dimensional CAD is not currently possible with any existing technology. This is just a new way to formulate the problem and maybe could produce a solution in the future.

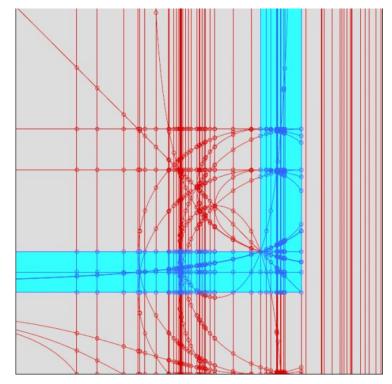


Figure 9: A two-dimensional CAD of just [x,y] point in configuration space.

Locally Guided Multiple Bi-RRT*

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.

Locally Guided Multiple Bi-RRT*

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Sampling in narrow space is done using bridge test.

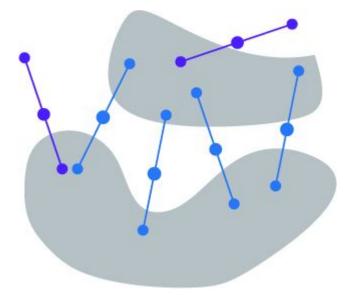


Figure 18: The principle of bridge test. The color in blue indicates passing the test, otherwise don't passing.

Locally Guided Multiple Bi-RRT*

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Sampling in narrow space is done using bridge test.
- K-means++ clustering algorithm is employed to obtain the Identification Points (IP).

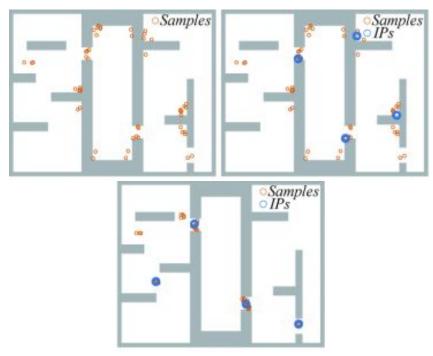


Figure 19: The improved bridge-test method with cluster analysis.

Locally Guided Multiple Bi-RRT*

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Sampling in narrow space is done using bridge test.
- K-means++ clustering algorithm is employed to obtain the Identification Points (IP).
- Generate local trees rooted at each IP and employ BRRT* to heuristically expand one by one.

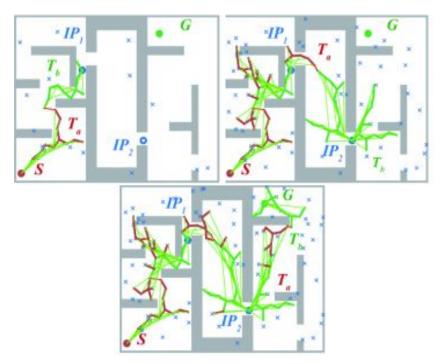


Figure 20: BRRT* applied between IPs and concatenated for a final path

Fast Bi-Directional Kinematic RRT

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Prunes nodes that have been failed to expand too many times.

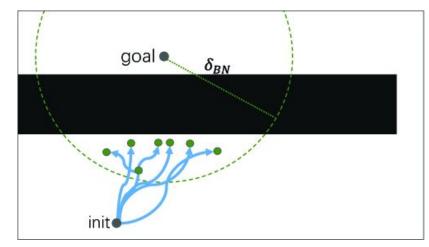


Figure 21: Nodes near obstacles failing to expand

4. J. Peng, Y. Chen, Y. Duan, Y. Zhang, J. Ji and Y. Zhang, "Towards an Online RRT-based Path Planning Algorithm for Ackermann-steering Vehicles," 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021, pp. 7407-7413, doi: 10.1109/ICRA48506.2021.9561207.

Fast Bi-Directional Kinematic RRT

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Prunes nodes that have been failed to expand too many times.
- Apply the idea of Rapid Random Vines to improve the performance of the algorithm for environments with narrow passages.

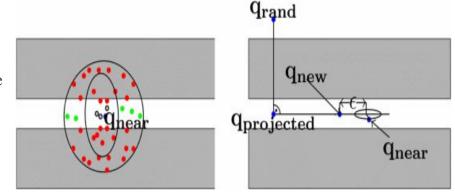


Figure 22: A vine node q_near is in a narrow passage and is not able to expand towards q_rand. After PCA has been conducted, the vine grows along the passage

4. J. Peng, Y. Chen, Y. Duan, Y. Zhang, J. Ji and Y. Zhang, "Towards an Online RRT-based Path Planning Algorithm for Ackermann-steering Vehicles," 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021, pp. 7407-7413, doi: 10.1109/ICRA48506.2021.9561207.

Adaptive Rapidly-Exploring Random Tree Connect

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Nodes are sampled in unexplored area as much as possible at the beginning and the rate of random sampling is gradually decreased.

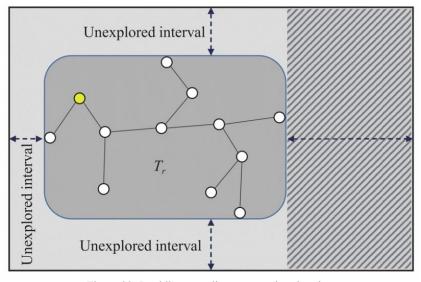


Figure 23: Rapidly expanding to unexplored regions

5. B. Li and B. Chen, "An Adaptive Rapidly-Exploring Random Tree," in IEEE/CAA Journal of Automatica Sinica, vol. 9, no. 2, pp. 283-294, February 2022, doi: 10.1109/JAS.2021.1004252.

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- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Nodes are sampled in unexplored area as much as possible at the beginning and the rate of random sampling is gradually decreased.
- If the initial search fails (upto certain iteration), partially connected nodes from start and goal is expanded locally.

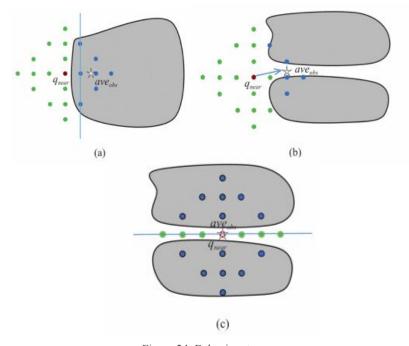


Figure 24: Behavior at narrow spaces

5. B. Li and B. Chen, "An Adaptive Rapidly-Exploring Random Tree," in IEEE/CAA Journal of Automatica Sinica, vol. 9, no. 2, pp. 283-294, February 2022, doi: 10.1109/JAS.2021.1004252.

Obstacle-Guided Sampling for RRTs

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- Gaussian obstacle-based sampling strategy is extended resulting in denser sample distribution near obstacles while retaining an underlying uniform spread over the free space.

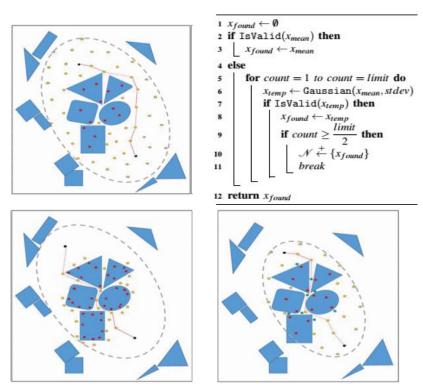


Figure 25: Gaussian obstacle-based sampling strategy applied over obstacles

6. Z. Meng, H. Qin, H. Sun, X. Shen and M. H. Ang, "Obstacle-guided informed planning towards robot navigation in cluttered environments," 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2017, pp. 332-337, doi: 10.1109/ROBIO.2017.8324439.

Obstacle-Guided Sampling for RRTs

- **Requirements**: *Map representing the environment, considers robot as a point.*
- Traditional RRTs consume high memory as well as time while finding a solution in cluttered environment.
- O Gaussian obstacle-based sampling strategy is extended resulting in denser sample distribution near obstacles while retaining an underlying uniform spread over the free space.
- O **Drawbacks**: Although these improvised RRTs are fast, these approaches do not account for the orientation or dimensions of the robot.

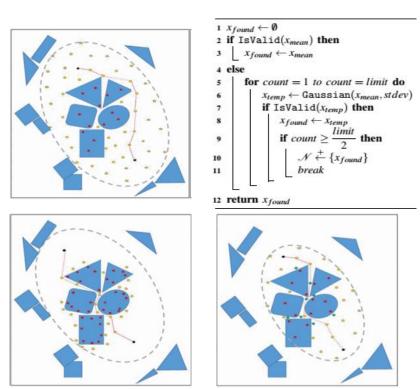


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Spline-Based Planning

- **Requirements**: Map representing the environment, dynamic obstacles information.
- Approach defines an optical control problem to find the trajectory in confined spaces and dynamic environment.

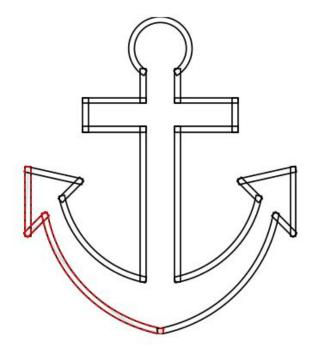


Figure 35: Spline planning in narrow spaces.

Spline-Based Planning

- **Requirements**: Map representing the environment, dynamic obstacles information.
- Approach defines an optical control problem to find the trajectory in confined spaces and dynamic environment.
- Given start and end points and obstacles position, the algorithm creates a potential field about the obstacles.

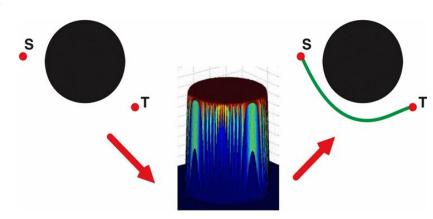


Figure 36: Generating spline by creating potential field.

Spline-Based Planning

- **Requirements**: Map representing the environment, dynamic obstacles information.
- Approach defines an optical control problem to find the trajectory in confined spaces and dynamic environment.
- O Given start and end points and obstacles position, the algorithm creates a potential field about the obstacles.
- The initial straight line path from 'S' to 'T' is expressed with 'via points' equally spaces and each point is pushed to a free space.

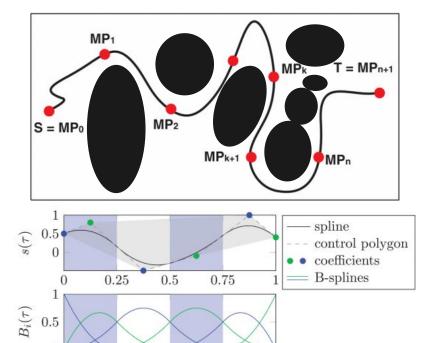


Figure 37: Optimizing spline globally.

0.75

0.25

0.5

Spline-Based Planning

- **Requirements**: Map representing the environment, dynamic obstacles information.
- Approach defines an optical control problem to find the trajectory in confined spaces and dynamic environment.
- Given start and end points and obstacles position, the algorithm creates a potential field about the obstacles.
- The initial straight line path from 'S' to 'T' is expressed with 'via points' equally spaces and each point is pushed to a free space.
- To account for obstacle movement, the constraints include a linear prediction model for every obstacle and the algorithm updates the spline continuously.
- O **Drawbacks**: Dynamic obstacles velocity and positions are previously known, which in reality has to be detected, which would pose a problem while using laser scans. Vehicle dimension isn't taken into account. Here, splines solve forwards motion planning.

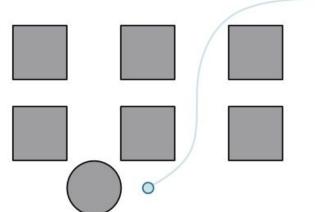


Figure 38: Spline planning with dynamic obstacles.

Model Predictive Path Planning Based on Projected C-Space

- **Requirements**: Map representing the environment, vehicle dimensions and kinematics.
- The vehicle model, and the other physical limitations such as the input bounds and safety constraints are considered in the optimization problem i.e. state equations of the system.
- Collision avoidance constraints are described in the projected configuration space transforming a rectangular collision area into a circle.

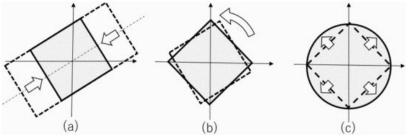


Figure 26: Coordinate transformation to map rectangular collision avoidance area to circular shape.

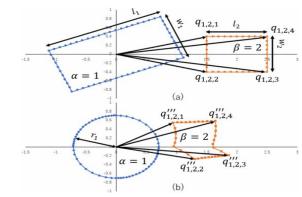


Figure 27: Transformation from rectangle to circle original rectangle collision area (a) is transformed to circle form (b).

8. T. Yamaguchi, T. Ishiguro, H. Okuda and T. Suzuki, "Model Predictive Path Planning for Autonomous Parking Based on Projected C-Space," 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), 2021, pp. 929-935, doi: 10.1109/ITSC48978.2021.9564599.

Model Predictive Path Planning Based on Projected C-Space

- **Requirements**: Map representing the environment, vehicle dimensions and kinematics.
- The vehicle model, and the other physical limitations such as the input bounds and safety constraints are considered in the optimization problem i.e. state equations of the plants.
- Collision avoidance constraints are described in the projected configuration space transforming a rectangular collision area into a circle.
- Finally, the optimization problem for the path planner based on the Model Predictive Control scheme is solved for reverse parking scenario.

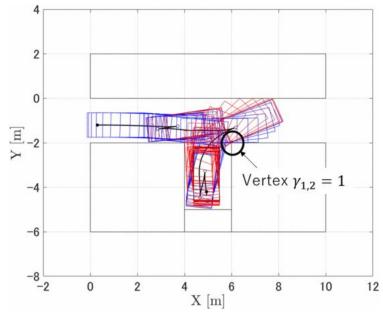


Figure 28: Vehicle position and posture in reverse parking.

8. T. Yamaguchi, T. Ishiguro, H. Okuda and T. Suzuki, "Model Predictive Path Planning for Autonomous Parking Based on Projected C-Space," 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), 2021, pp. 929-935, doi: 10.1109/ITSC48978.2021.9564599.

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- The vehicle model, and the other physical limitations such as the input bounds and safety constraints are considered in the optimization problem i.e. state equations of the plants.
- Collision avoidance constraints are described in the projected configuration space transforming a rectangular collision area into a circle.
- Finally, the optimization problem for the path planner based on the Model Predictive Control scheme is solved for reverse parking scenario.
- O **Drawbacks**: Obstacles are to be know and in polygon form to apply transformation. Works well in short range planning, as the number of obstacles increases so does the complexity.

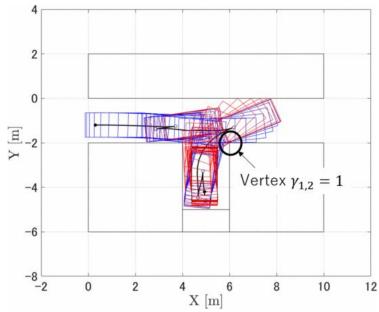


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Multistage Hybrid A* and Numerical Optimal Control

- **Requirements**: *Map representing the environment, robot's dimensions.*
- O Given the start and end points along with the obstacles, the map is discretized to an occupancy grid.

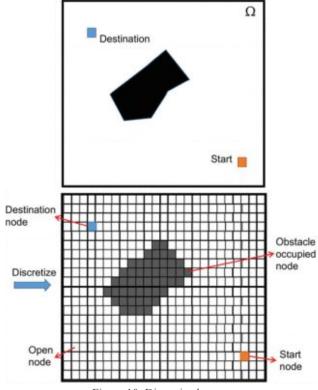


Figure 10: Discretized map.

Multistage Hybrid A* and Numerical Optimal Control

- **Requirements**: *Map representing the environment, robot's dimensions.*
- Given the start and end points along with the obstacles, the map is discretized to an occupancy grid.
- O Hybrid A* initially find a path using regular A*, then finds narrow passages and divides the path into segments, kinematically feasible subpaths (Reeds–Shepp curves) are found and finally are combined together.
- Improved Safe Travel Corridor (STC) Based Trajectory
 Optimization is used to solve the optimal control problem.
 First-order explicit Runge-Kutta method is applied to discretize and
 Interior Point Method (IPM) is chosen as the NLP solver.

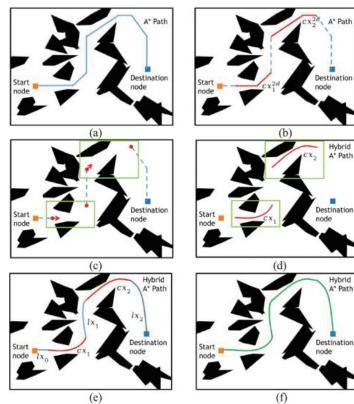


Figure 11: Schematics on the steps in the multistage hybrid A* algorithm.

Multistage Hybrid A* and Numerical Optimal Control

- **Requirements**: Map representing the environment, robot's dimensions.
- O Given the start and end points along with the obstacles, the map is discretized to an occupancy grid.
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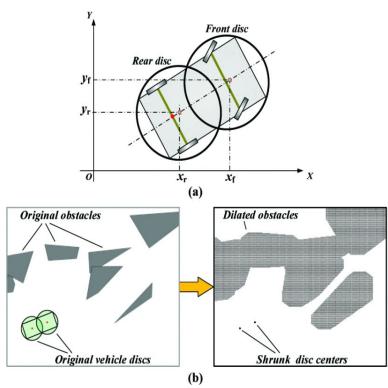


Figure 12: Visualizing the altered environment and robot.

Multistage Hybrid A* and Numerical Optimal Control

- **Requirements**: Map representing the environment, robot's dimensions.
- Given the start and end points along with the obstacles, the map is discretized to an occupancy grid.
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- Improved Safe Travel Corridor (STC) Based Trajectory
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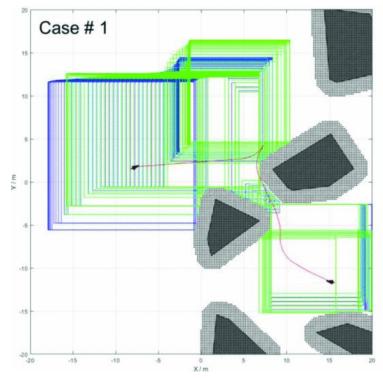


Figure 13: Applied STC to both ends of the vehicle.

Multistage Hybrid A* and Numerical Optimal Control

- **Requirements**: Map representing the environment, robot's dimensions.
- Given the start and end points along with the obstacles, the map is discretized to an occupancy grid.
- O Hybrid A* initially find a path using regular A*, then finds narrow passages and divides the path into segments, kinematically feasible subpaths (Reeds–Shepp curves) are found and finally are combined together.
- Improved Safe Travel Corridor (STC) Based Trajectory
 Optimization is used to solve the optimal control problem.

 First-order explicit Runge-Kutta method is applied to discretize and Interior Point Method (IPM) is chosen as the NLP solver.
- O **Drawbacks**: Initial coarse path could lead to local minimas. To obtain safer path the number of STCs should be increased which would increase complexity.

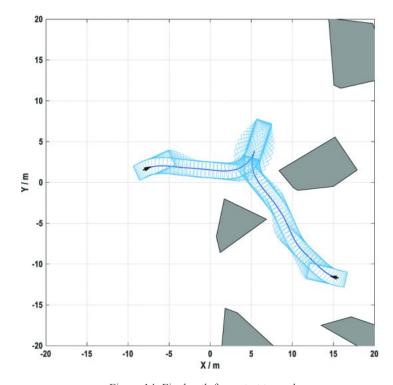


Figure 14: Final path from start to goal.

Random Tree - C*CS Planner

- **Requirements**: *Map representing the environment, vehicle dimensions and kinematics, motion primitives.*
- Uses sampling-based geometric planning and approximation by a topological steering method in configuration space (Triangular cell decomposition).
- Bi RRT is performed where the node is randomly placed anywhere on the neighbouring cells. If there is no clear path, sub branches are created in the current cell.

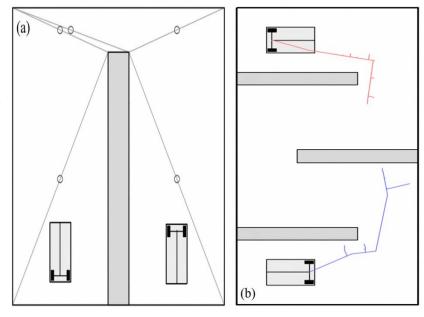


Figure 29: Triangular decomposition and Bi RRTs.

10. Á. Nagy, G. Csorvási and D. Kiss, "Path planning and control of differential and car-like robots in narrow environments," 2015 IEEE 13th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2015, pp. 103-108, doi: 10.1109/SAMI.2015.7061856.

Random Tree - C*CS Planner

- **Requirements**: Map representing the environment, vehicle dimensions and kinematics, motion primitives.
- Uses sampling-based geometric planning and approximation by a topological steering method in configuration space (Triangular cell decomposition).
- O Bi RRT is performed where the node is randomly placed anywhere on the neighbouring cells. If there is no clear path, sub branches are created in the current cell.
- Primary global path planner consists only of straight motion and turning in place primitives.

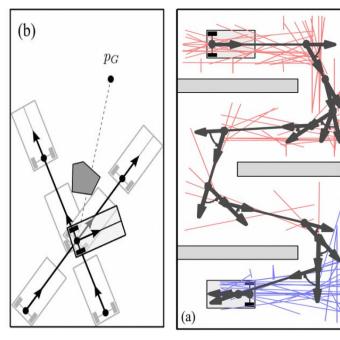


Figure 30: Bi directional RRTs and motion primitives.

10. Á. Nagy, G. Csorvási and D. Kiss, "Path planning and control of differential and car-like robots in narrow environments," 2015 IEEE 13th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2015, pp. 103-108, doi: 10.1109/SAMI.2015.7061856.

Random Tree - C*CS Planner

- **Requirements**: Map representing the environment, vehicle dimensions and kinematics, motion primitives.
- Uses sampling-based geometric planning and approximation by a topological steering method in configuration space (Triangular cell decomposition).
- Primary global path planner consists only of straight motion and turning in place primitives.
- Bi RRT is performed where the node is randomly placed anywhere on the neighbouring cells. If there is no clear path, sub branches are created in the current cell.
- A local C*CS planner is applied to obtain a secondary path containing straight segments and circular arcs of given lower bounded radii (CCS and SCS paths).

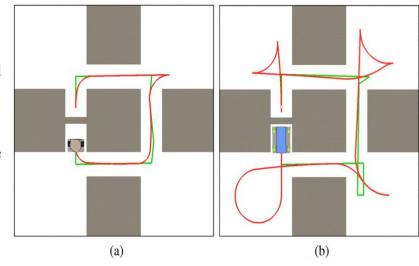


Figure 31: The RTR path (green) and its C*CS approximation (red) for (a) differential and (b) car-like robots.

10. Á. Nagy, G. Csorvási and D. Kiss, "Path planning and control of differential and car-like robots in narrow environments," 2015 IEEE 13th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2015, pp. 103-108, doi: 10.1109/SAMI.2015.7061856.

Random Tree - T*TS Planner

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- Uses sampling-based geometric planning and approximation by a topological steering method in configuration space (Triangular cell decomposition).
- Primary global path planner consists only of straight motion and turning in place primitives.
- O Bi RRT is performed where the node is randomly placed anywhere on the neighbouring cells. If there is no clear path, sub branches are created in the current cell.
- A local T*TS planner is applied to obtain a secondary path (clothoids) containing straight segments 'S' and CC-turn 'T' that can have zero sharpness and curvature (TTS and STS paths).

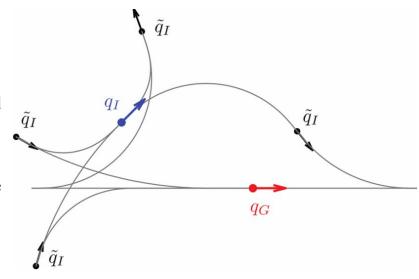
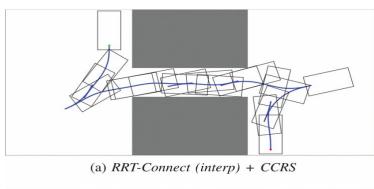


Figure 32: There is a number of T*TS solutions between two configurations.

D. Kiss and D. Papp, "Effective navigation in narrow areas: A planning method for autonomous cars," 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2017, pp. 000423-000430, doi: 10.1109/SAMI.2017.7880346.

Random Tree - T*TS Planner

- **Requirements**: *Map representing the environment, vehicle dimensions and kinematics, motion primitives.*
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- A local T*TS planner is applied to obtain a secondary path (clothoids) containing straight segments 'S' and CC-turn 'T' that can have zero sharpness and curvature (TTS and STS paths).
- **Drawbacks**: Cannot handle dynamic environment. Motion primitives should have higher resolution as area gets narrower.



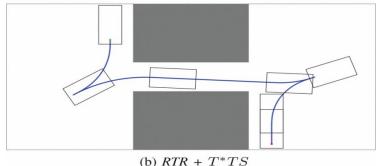


Figure 33: Crossing a narrow corridor.

D. Kiss and D. Papp, "Effective navigation in narrow areas: A planning method for autonomous cars," 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2017, pp. 000423-000430, doi: 10.1109/SAMI.2017.7880346.

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- **Drawbacks**: Cannot handle dynamic environment. Motion primitives should have higher resolution as area gets narrower.

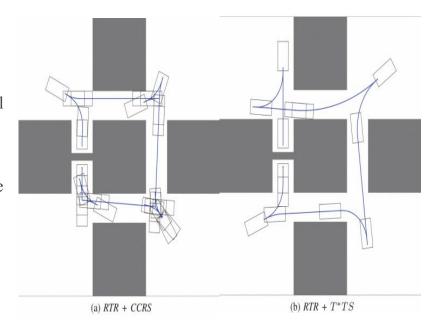


Figure 34: Crossing three narrow corridors.

D. Kiss and D. Papp, "Effective navigation in narrow areas: A planning method for autonomous cars," 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2017, pp. 000423-000430, doi: 10.1109/SAMI.2017.7880346.

Shape-Aware Lifelong A* Planning

• **Requirements**: Configuration space map with obstacles expanded to the width of the robot.

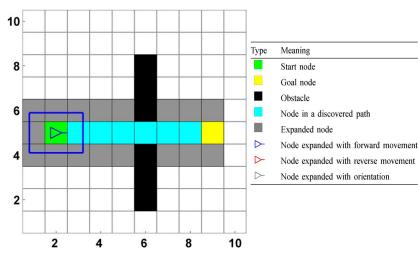


Figure 15: Vehicle unable to pass through a passage that is too narrow

Shape-Aware Lifelong A* Planning

- **Requirements**: Configuration space map with obstacles expanded to the width of the robot.
- The child nodes include orientation of the robot and translation (forward and reverse).
- While finding child nodes it checks collision with obstacles from current to child node.

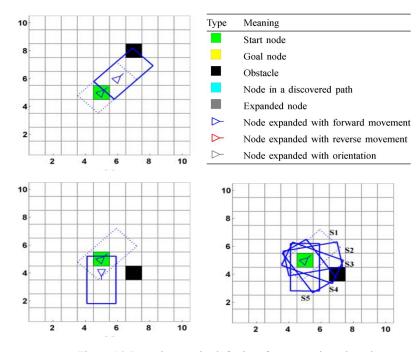


Figure 16: Procedure to check for interference against obstacles.

Shape-Aware Lifelong A* Planning

- **Requirements**: Configuration space map with obstacles expanded to the width of the robot.
- The child nodes include orientation of the robot and translation (forward and reverse).
- While finding child nodes it checks collision with obstacles from current to child node.
- Modified A*, including an algorithm to check for interference against obstacles uses Manhattan distances as heuristic.

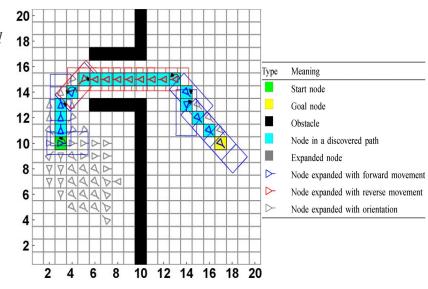


Figure 17: path planner generates a collision-free path, including a reverse movement at coordinates

Shape-Aware Lifelong A* Planning

- **Requirements**: Configuration space map with obstacles expanded to the width of the robot.
- The child nodes include orientation of the robot and translation (forward and reverse).
- While finding child nodes it checks collision with obstacles from current to child node.
- Modified A*, including an algorithm to check for interference against obstacles uses Manhattan distances as heuristic.
- **Drawbacks**: Complexity increases with increase in resolution and discretization of rotation. Suitable for short range navigation.

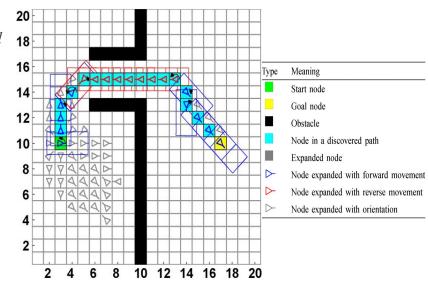


Figure 17: path planner generates a collision-free path, including a reverse movement at coordinates

Configuration-Aware Model Predictive Motion Planning

- Convex polygons are used to express the configuration of the robots, obstacles, and walls.
- Farkas' lemma is applied to express the collision avoidance constraints
- Motion Planning based on Receding Horizon. The model of the robot is discretized by the Euler method and Interior Point Optimizer is used to solve the problem (nonlinear MPC)
- The collision check will be done for each obstacle, therefore complexity would increase while working with a point cloud

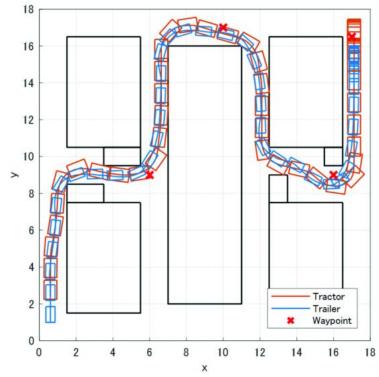


Figure 32: Configuration-Aware Model Predictive Motion Planning

13. N. Ito, H. Okuda, S. Inagaki and T. Suzuki, "Configuration-aware Model Predictive Motion Planning in Narrow Environment for Autonomous Tractor-trailer Mobile Robot," IECON 2021 – 47th Annual Conference of the IEEE Industrial Electronics Society, 2021, pp. 1-7, doi: 10.1109/IECON48115.2021.9589596.

Optimization-Based Maneuver Planning

- A* algorithm is deployed to search for a sequence of nodes connecting the initial and terminal locations in the grid map
- The maneuver planning scheme for the vehicle is formulated as an Optimal Control Problem which consists of a cost function and three types of constraints (Kinematic, boundary and collision)
- From the reference path, Safe Travel Corridors are constructed to simplify the collision-avoidance constraints
- Trust-Region-Based Maneuver Optimization (TRMO) is used to solve the optimization problem

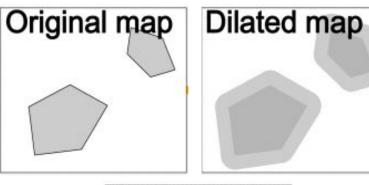




Figure 33: Map representation for Optimization-Based Maneuver Planning

14. B. Li, L. Li, T. Acarman, Z. Shao and M. Yue, "Optimization-Based Maneuver Planning for a Tractor-Trailer Vehicle in a Curvy Tunnel: A Weak Reliance on Sampling and Search," in IEEE Robotics and Automation Letters, vol. 7, no. 2, pp. 706-713, April 2022, doi: 10.1109/LRA.2021.3131693.

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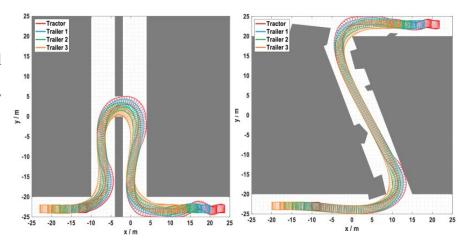


Figure 34: Optimization-Based Maneuver Planning in narrow spaces

14. B. Li, L. Li, T. Acarman, Z. Shao and M. Yue, "Optimization-Based Maneuver Planning for a Tractor-Trailer Vehicle in a Curvy Tunnel: A Weak Reliance on Sampling and Search," in IEEE Robotics and Automation Letters, vol. 7, no. 2, pp. 706-713, April 2022, doi: 10.1109/LRA.2021.3131693.

Modified A* Path-Planning

- Traditional A* algorithm doesn't account for the size of the robot
- Obstacles are enlarged to the equivalent size i.e. (2n+1) size of the cell
- Can only apply to square shaped robots
- Computationally costly if resolution of the map is increased

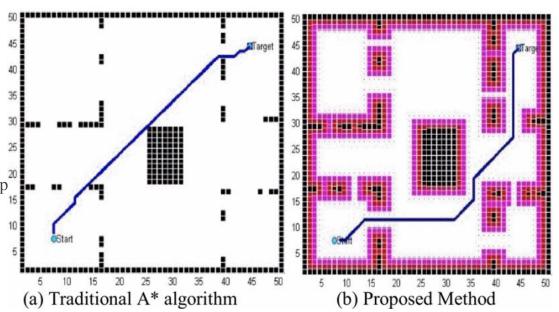
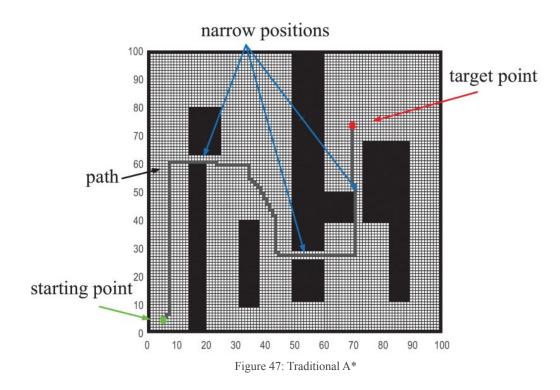


Figure 46: Modified A* Path-Planning

15. J. K. Goyal and K. S. Nagla, "A new approach of path planning for mobile robots," 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2014, pp. 863-867, doi: 10.1109/ICACCI.2014.6968200.

Improved A* Algorithm

 Traditional A* algorithm creates a rough and uneven path



Improved A* Algorithm

- Traditional A* algorithm creates a rough and uneven path
- Compressing the map resolution avoids narrow gaps

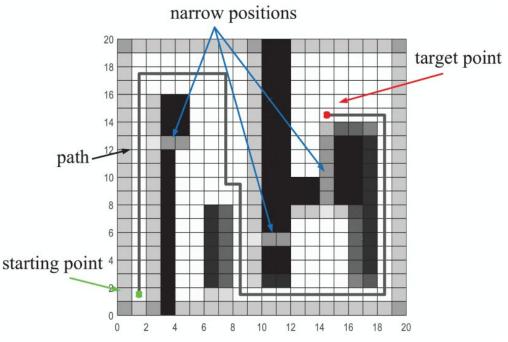


Figure 48: Path-Planning with reduced resolution

Improved A* Algorithm

- Traditional A* algorithm creates a rough and uneven path
- Compressing the map resolution avoids narrow gaps
- Path is then smoothened by recursively finding nodes on each line that shortens the path

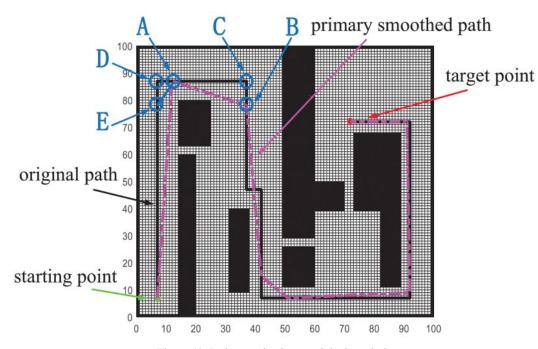


Figure 49: Path smoothening at original resolution

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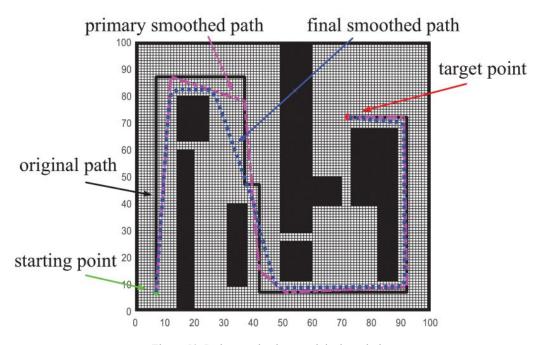


Figure 50: Path smoothening at original resolution

Improved A* Algorithm

- Traditional A* algorithm creates a rough and uneven path
- Compressing the map resolution avoids narrow gaps
- Path is then smoothened by recursively finding nodes on each line that shortens the path
- Computationally expensive for long range planning

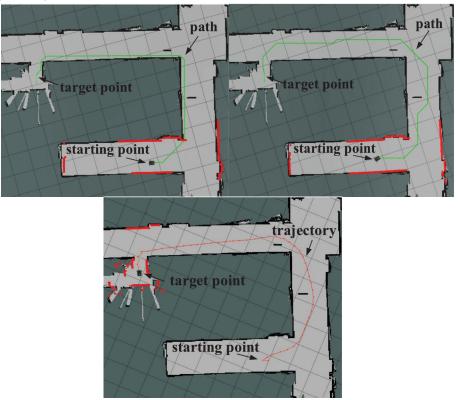


Figure 51: Path planning with Improved A* Algorithm

Hybrid A* Potential Field Method

- Takes the best of both methods to reduce the overall path cost
- O To avoid oscillations in narrow spaces an Adaptive Moment Estimation (ADAM) which is a variation of gradient descent method is used to optimize the potential field method

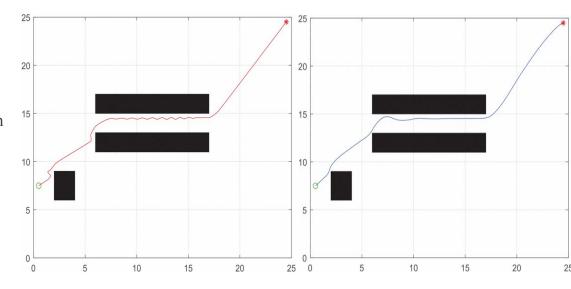


Figure 52: Oscillations at narrows spaces using potential fields

17. H. Wang, Z. Wang, L. Yu, Q. Wang and C. Liu, "A Hybrid Algorithm For Robot Path Planning," 2018 IEEE International Conference on Mechatronics and Automation (ICMA), 2018, pp. 986-990, doi: 10.1109/ICMA.2018.8484297.

Hybrid A* Potential Field Method

- Takes the best of both methods to reduce the overall path cost
- O To avoid oscillations in narrow spaces an Adaptive Moment Estimation (ADAM) which is a variation of gradient descent method is used to optimize the potential field method
- A* is first applied to a pixelated map to get an initial path after which it is smoothened using the potential field method

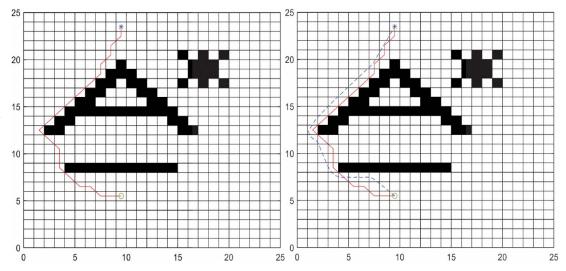


Figure 53: Hybrid A* Potential Field Method applied to grid map

17. H. Wang, Z. Wang, L. Yu, Q. Wang and C. Liu, "A Hybrid Algorithm For Robot Path Planning," 2018 IEEE International Conference on Mechatronics and Automation (ICMA), 2018, pp. 986-990, doi: 10.1109/ICMA.2018.8484297.

Hybrid A* Potential Field Method

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- A* is first applied to a pixelated map to get an initial path after which it is smoothened using the potential field method
- Discretization and map resolution still affects the complexity

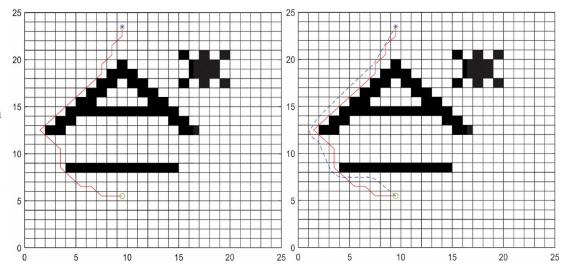


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New Global Path Planning Strategy

 Skeletonization is performed on a pixel map using a distance field map combined with thinning

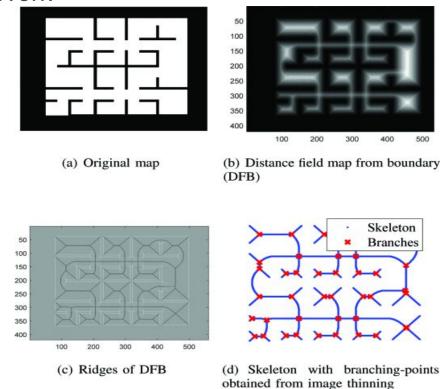


Figure 54: Skeletonization is performed on a pixel map

New Global Path Planning Strategy

- Skeletonization is performed on a pixel map using a distance field map combined with thinning
- Allowable speed and Cost-to-Go parameters are used to defined nodes and edges

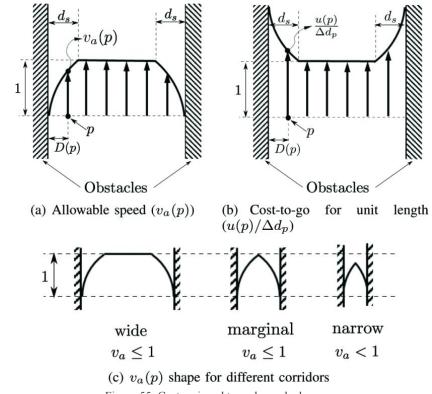


Figure 55: Cost assigned to nodes and edges

New Global Path Planning Strategy

- Skeletonization is performed on a pixel map using a distance field map combined with thinning
- Allowable speed and Cost-to-Go parameters are used to defined nodes and edges
- The map is then represented as a hierarchical graph

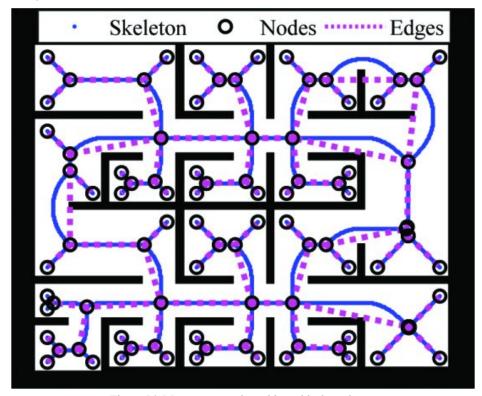


Figure 56: Map represented as a hierarchical graph

New Global Path Planning Strategy

- Skeletonization is performed on a pixel map using a distance field map combined with thinning
- Allowable speed and Cost-to-Go parameters are used to defined nodes and edges
- The map is then represented as a hierarchical graph
- Finally the path planner takes the time taken by the robot to safely reach the goal for optimization

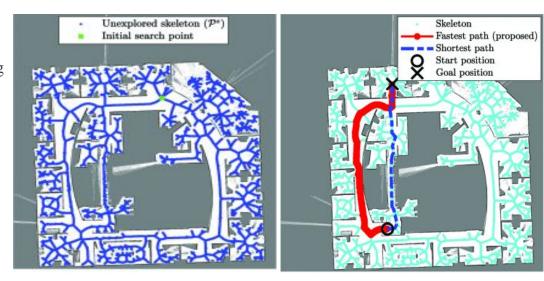


Figure 57: Global Path Planning Strategy applied in real environment

Rapid Random Tree - C*CS Planner

- **Requirements**: Geometric map, vehicle dimensions and kinematics, motion primitives
- Triangular cell decomposition applied on geometric map
- Bi RRT performed with steps to neighbouring cells and motion primitives are used to connect nodes

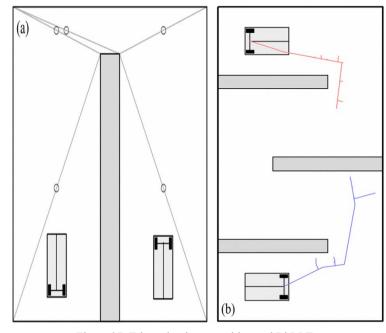
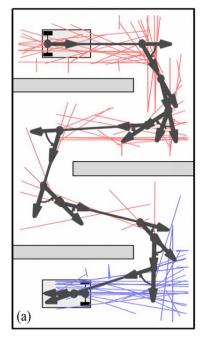


Figure 27: Triangular decomposition and Bi RRTs.

8. Á. Nagy, G. Csorvási and D. Kiss, "Path planning and control of differential and car-like robots in narrow environments," 2015 IEEE 13th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2015, pp. 103-108, doi: 10.1109/SAMI.2015.7061856.

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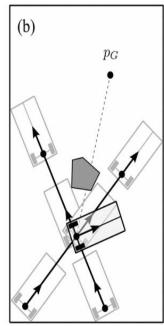


Figure 28: Bi directional RRTs and motion primitives.

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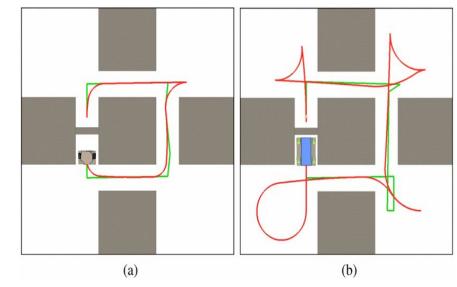


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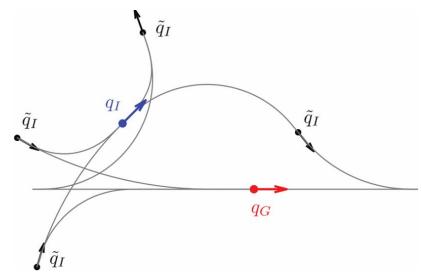


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- **T*TS planner** applied to obtain a secondary path (clothoids) containing straight segments 'S' and CC-turn 'T' that can have zero sharpness and curvature (TTS and STS paths)
- **Drawbacks**: Requires geometric information of environment. More motion primitives needed for narrower areas.

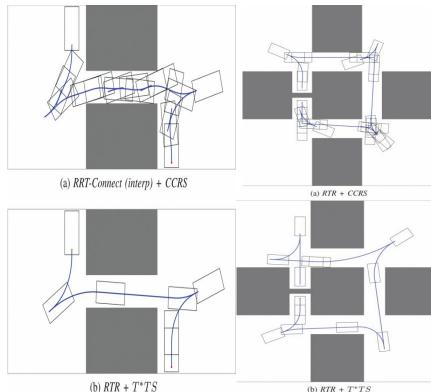


Figure 31: Crossing a narrow corridor and three narrow corridors.

9. D. Kiss and D. Papp, "Effective navigation in narrow areas: A planning method for autonomous cars," 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 2017, pp. 000423-000430, doi: 10.1109/SAMI.2017.7880346.