

AC555
Obstacle Avoidance

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- 4 Perturbations
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Idea

Improving the Obstacle Avoidance Algorithm:

- Generation of **ellipses** around the obstacles.
- Creation of **moving obstacles** by adding constant velocities.
- Implement the **MPC controller** on the TurtleBot and solving the optimization problem.

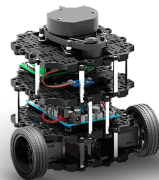


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Obstacles

We defined each obstacle's vertices and created them using an existing library in Python, named *Polygon*.

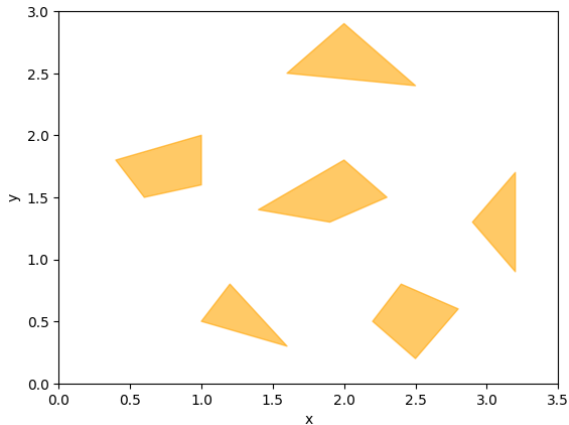
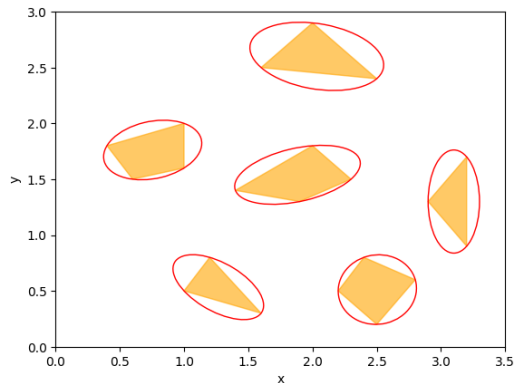


Figure: Polygons

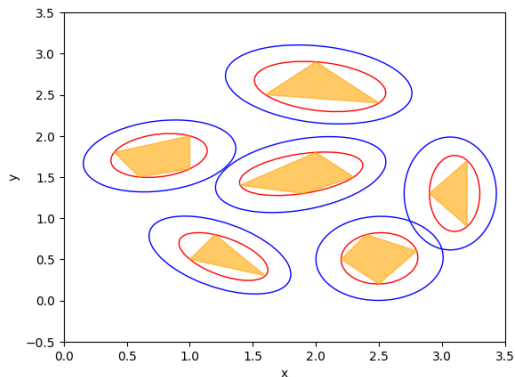
Ellipses

The Minimum Volume Enclosing Ellipsoid (MVEE) algorithm is used to find the smallest ellipsoid that encloses a given set of points in n-dimensional space. This ellipsoid is expressed as:

$$\mathcal{E} = \left\{ \mathbf{x} \in \mathbb{R}^n \mid (\mathbf{x} - \mathbf{c})^T \mathbf{A} (\mathbf{x} - \mathbf{c}) \leq 1 \right\}$$



(a) First Ellipses



(b) Enlarged Ellipses

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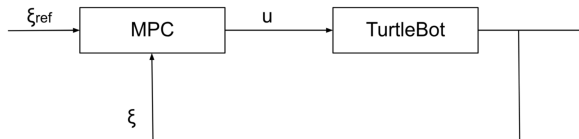
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 - Mathematical Model
 - Nonlinear dynamics
 - The problems
 - Weight Matrices
 - Results
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Mathematical Model

The dynamics of the robot with respect to the control input vectors are:

$$\zeta = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad \dot{\zeta} = \begin{bmatrix} V \cos \theta \\ V \sin \theta \\ \omega \end{bmatrix} \quad u = \begin{bmatrix} V \\ \omega \end{bmatrix}$$

The controller receives data concerning the current system's state and, based on a target point, set by the operator, computes the optimal control inputs.



Dynamics of the system and Cost

The dynamics are nonlinear and the *sampling period* is used as the discrete system provides the state at equally divided samples of time ($T_s = 0.1$):

$$x(k+1) = x(k) + T_s * V(k) \cos \theta(k)$$

$$y(k+1) = y(k) + T_s * V(k) \sin \theta(k)$$

$$\theta(k+1) = \theta(k) + T_s * \omega(k)$$

The predictive control feedback law is computed by minimizing a predicted performance cost, which is defined in terms of the predicted sequences \mathbf{u} , \mathbf{x} . The predicted cost has the general form:

$$J(x_k, \mathbf{u}_k) = x_N^\top P x_N + \sum_{i=0}^{N-1} (||x_{i|k} - x_{ref}||_Q^2 + ||u_{i|k}||_R^2)$$

Optimization cost function for static obstacles

The optimal control sequence for the problem of minimizing the predicted cost is denoted $\mathbf{u}_N^*(x_k)$ and we can rewrite the optimization cost function as:

$$\mathbf{u}_N^* = \arg \min_{\mathbf{u}_N} \left(x_N^\top P x_N + \sum_{k=0}^{N-1} \left((x_k - x_{ref})^\top Q (x_k - x_{ref}) + u_k^\top R u_k \right) \right)$$

$$\text{s.t.} \quad x_{k+1} = x_k + T_s * f(x_k, u_k),$$

$$x_{min} \leq x_{k+1} - x_k \leq x_{max},$$

$$u_{min} \leq u_k \leq u_{max},$$

$$(\mathbf{x}_{k+1} - \mathbf{c}_{obs_i})^\top \mathbf{A}_{obs_i} (\mathbf{x}_{k+1} - \mathbf{c}_{obs_i}) > 1,$$

$$\mathbf{A}_{obs_i} \in \mathbb{R}^{n \times n}, \mathbf{c}_{obs_i} \in \mathbb{R}^n, i \in N_{obstacles}.$$

Optimization cost function for moving obstacles

The optimal control sequence for the problem of minimizing the predicted cost while the obstacles are moving is denoted $\mathbf{u}_N^*(x_k)$ and we can rewrite the optimization cost function as:

$$\mathbf{u}_N^* = \arg \min_{u_N} \left(x_N^\top P x_N + \sum_{k=0}^{N-1} \left((x_k - x_{ref})^\top Q (x_k - x_{ref}) + u_k^\top R u_k \right) \right)$$

$$\text{s.t.} \quad x_{k+1} = x_k + T_s * f(x_k, u_k),$$

$$x_{min} \leq x_{k+1} - x_k \leq x_{max},$$

$$u_{min} \leq u_k \leq u_{max},$$

$$\left(x_{k+1} - \mathbf{c}_{obs_{i|k}} \right)^\top \mathbf{A}_{obs_{i|k}} \left(x_{k+1} - \mathbf{c}_{obs_{i|k}} \right) > 1,$$

$$\mathbf{A}_{obs_{i|k}} \in \mathbb{R}^{n \times n}, \mathbf{c}_{obs_{i|k}} \in \mathbb{R}^n, i \in N_{obstacles}.$$

Weight Matrices

The weight matrices that we have chosen after multiple tests are:

$$Q = \begin{bmatrix} 10 & 0 & 0 \\ 0 & 10 & 0 \\ 0 & 0 & 10 \end{bmatrix}$$

$$R = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$$

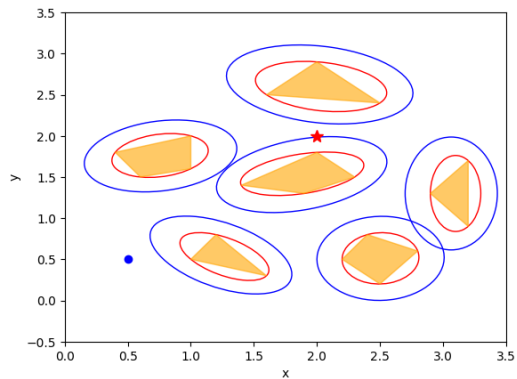
$$P = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 100 \end{bmatrix},$$

with $N_{pred} = 100$.

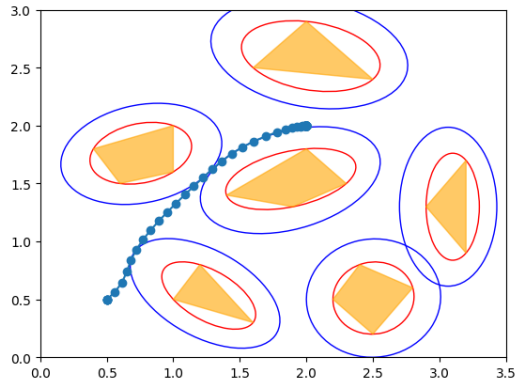
Computation time

The computation time for solving the problem is 10 seconds.

Results



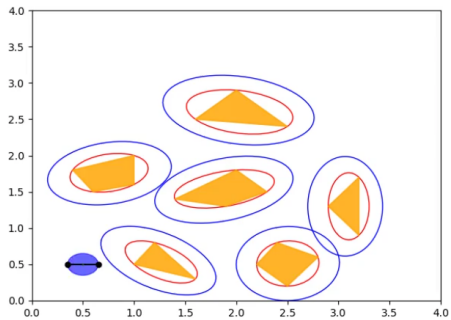
(a) Initial and Goal points



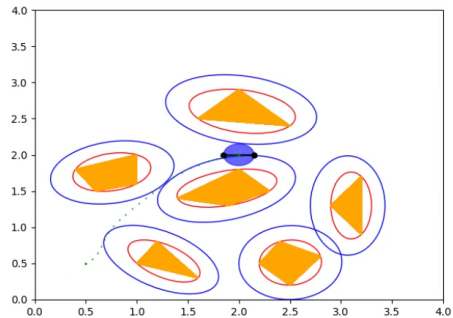
(b) Computed Trajectory

Figure: Static Obstacles

Results



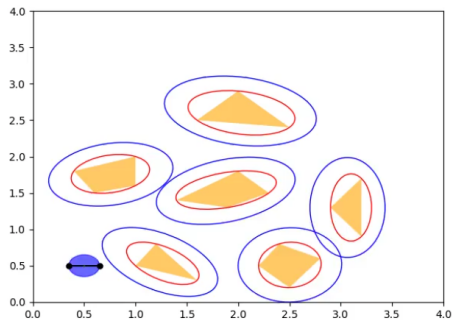
(a) Initial position



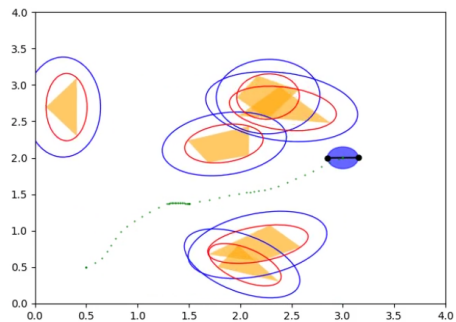
(b) Final Position

Figure: Static Obstacles

Results



(a) Initial position



(b) Final Position

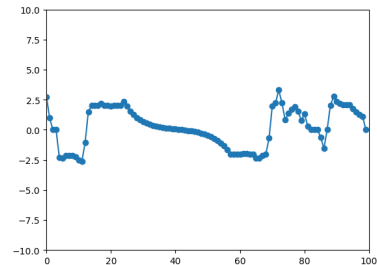
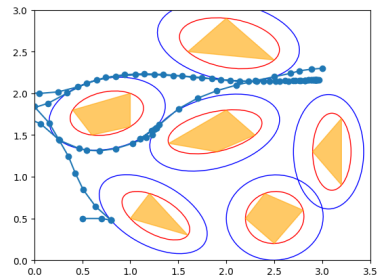
Figure: Dynamic Obstacles

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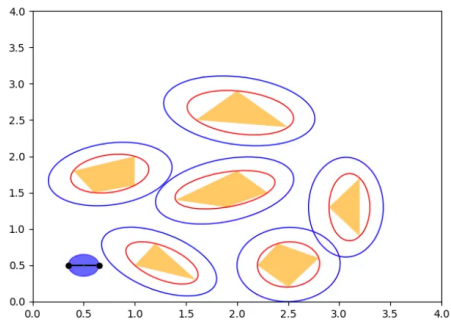
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Perturbations

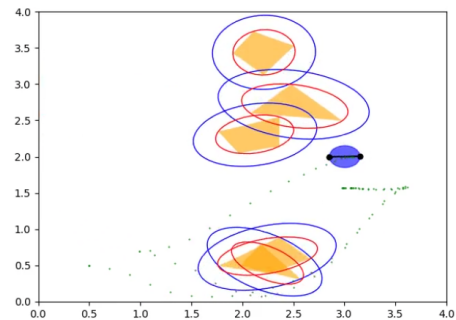
- Addition of noisy perturbations on the first state of x_k .
- ξ_{ref}
- Relaxing the input constraints.
- Random perturbations between $[-0.1, 0.1]$.



Results



(a) Initial position



(b) Final Position

Figure: Dynamic Obstacles

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Conclusion and Future Directions

Future Directions:

- Implementation of two robots that go to the same goal point.
- Making one robot follow another one while avoiding obstacles.

Conclusions:

- Implementation of two MPC problems.
- Creating an obstacle avoidance algorithm for moving objects.
- Understanding of how random perturbations might affect the behavior of the robot.

Thank you for your time!