

State-space Modeling And Control For Differential Drive Warehouse Robots

by

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AIM AND OBJECTIVE

AIM:

- The primary aim of the project is to develop a state space model for the differential drive robots in warehouse setting.

OBJECTIVE:

- Designing of state space representation of warehouse robot.
- Calculating and optimizing gain for the system.
- Analyzing the stability of the system to ensure consistent behavior.
- Designing of controller based on precise calculation and requirements.
- Designing observer for the robot to estimate unmeasured states or disturbances.



STATE SPACE MODEL

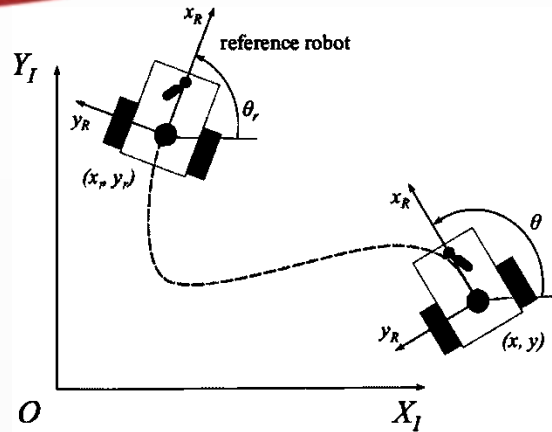


Figure 01: Differential Drive Robot in X-Y Plane

Where,

Kinematic Equations are as follows: $\dot{x} = v \cos(\theta)$

$$\dot{y} = v \sin(\theta)$$

$$\dot{\theta} = u_2 = \frac{v_R - v_L}{d}$$

$$\dot{v} = u_1 = \frac{v_R + v_L}{2}$$

State Variables are:

$$x = \begin{bmatrix} x \\ y \\ \theta \\ v \end{bmatrix}$$

State-Space Model:

$$\dot{x} = Ax + Bu \text{ and } y = Cx$$

$$\text{Where } A = \begin{bmatrix} 0 & 0 & -v \sin(\theta_0) & \cos(\theta_0) \\ 0 & 0 & v \cos(\theta_0) & \sin(\theta_0) \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}, C = [I_4], D = [0]$$

Key Components:

State Variables:

- x : Position of the robot in the x – direction.
- y : Position of the robot in the y – direction.
- θ : Heading angle (orientation) of the robot.
- v : Linear velocity of the robot.

Inputs:

- u_1 : Linear acceleration
- u_2 : Angular Velocity

FEEDBACK GAIN

Considering following for the desired performance:

- Speed of the response: 1sec/2sec.
- Damping Ratio: 0.7.
- Natural Frequency: 5 rad/sec.

Using the second-order system characteristics deriving the poles:

$$\begin{aligned} \text{Poles} &= -\zeta\omega_n \pm j\omega_n\sqrt{1-\zeta^2} \\ -\zeta\omega_n &= -0.7 \times 5 = -3.5 \dots \text{Real Part} \end{aligned}$$

$$\begin{aligned} \omega_n\sqrt{1-\zeta^2} &= 5\sqrt{1-0.7^2} \approx 5 \times 0.714 \\ &= 3.57 \dots \text{Imaginary part} \end{aligned}$$

$$\text{Poles} \approx -3.5 \pm j3.57$$

Additional real poles for faster settling
Real Poles = -5 (for faster response)

After simulation in MATLAB the following gain matrix K was obtained,

$$\begin{bmatrix} 0.0088 \times 10^{-3} & 4.3998 \times 10^{-3} & 0.8812 \times 10^{-3} & 0.0068 \times 10^{-3} \\ 0.0089 \times 10^{-3} & 4.3867 \times 10^{-3} & 0.8761 \times 10^{-3} & 0.0068 \times 10^{-3} \end{bmatrix}$$

```
desired_poles = [-3.5 + 3.57j, -3.5 - 3.57j, -5, -5];
```

```
K = place(A, B, desired_poles);
```

```
disp('Feedback Gain Matrix K:');
```

```
Feedback Gain Matrix K:
```

```
disp(K);
```

```
1.0e+03 *
```

```
0.0088    4.3998    0.8812    0.0068
0.89      4.3867    0.8761    0.0068
```


VEHICLE DYNAMICS TESTING

```
x0 = 0; % Initial x position
y0 = 0; % Initial y position
theta0 = 0; % Initial heading angle (in radians)
v0 = (v_R + v_L) / 2; % Initial velocity (average of both wheels)
initial_state = [x0; y0; theta0; v0];
```

```
[t, states] = ode45(@(t, x) robot_dynamics_circular(t, x, d, v_R, v_L), t_span, initial_state);
```

```
% Function definition for robot dynamics in a circular path
function dxdt = robot_dynamics_circular(t, x, d, v_R, v_L)
    theta = x(3);
    v = x(4);
```

```
% System dynamics
```

```
dxdt = zeros(4,1); % Initialize the state derivative vector
```

```
dxdt(1) = v * cos(theta); % x_dot
```

```
dxdt(2) = v * sin(theta); % y_dot
```

```
dxdt(3) = (v_R - v_L) / d; % theta_dot (angular velocity)
```

```
dxdt(4) = (v_R + v_L) / 2; % v_dot (linear velocity)
```

```
end
```

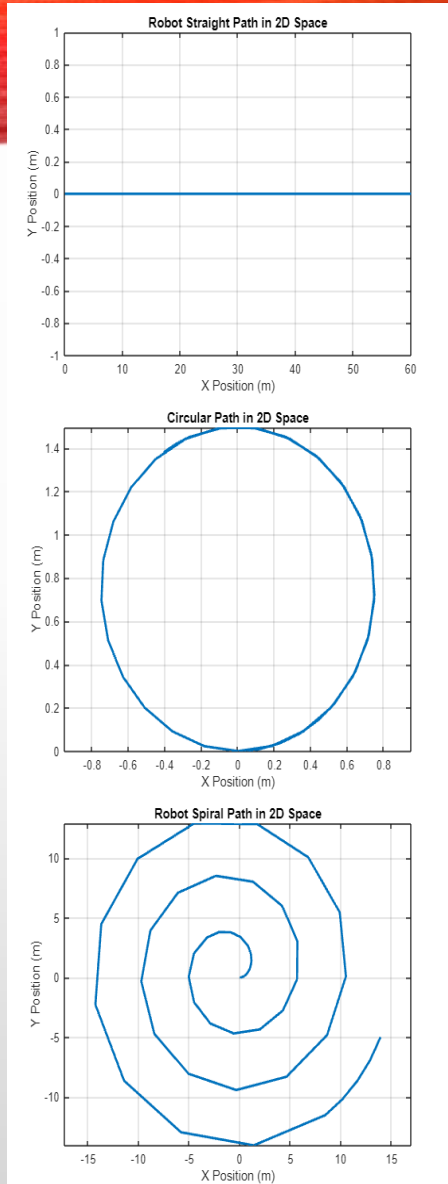


Figure 02: Test output for Vehicle Dynamics.

LQR CONTROLLER DESIGN

The objective of the LQR controller design is to minimize the cost function where

$$J = \int_0^{\infty} (x^T Q x + u^T R u) dt$$

Q: Penalizes deviations in states (prioritize position accuracy).

$$Q = \text{diag}(q_x, q_y, q_\theta, q_v)$$

$$Q = \text{diag}(10, 10, 1, 1)$$

R: Penalizes control effort (avoid excessive actuator use).

$$R = \text{diag}(r_w, r_a)$$

$$R = \text{diag}(1, 1)$$

Algebraic Riccati Equation yields the P matrix which is used to determine the gain matrix K.

$$A^T P + P A - P B R^{-1} B^T P + Q = 0$$

$$K = R^{-1} B^T P$$

$$\text{where } K = \begin{bmatrix} 3.1106 & 0.5693 & 0.4838 & 2.8204 \\ -0.5693 & 3.1106 & 2.6433 & 0.4838 \end{bmatrix}$$

closed loop eigenvalues:

$$-1.4060 \pm 1.3925i \text{ and } -1.3259 \pm 0.8921i$$

```
Q = diag([10, 10, 1, 1]);
R = diag([1, 1]);
P = care(A, B, Q, R);
K = R \ (B' * P); % Equivalent to inv(R) * B' * P
disp('LQR Gain Matrix (K):');
LQR Gain Matrix (K):
disp(K);
```

```
3.1106    0.5693    0.4838    2.8204
-0.5693    3.1106    2.6433    0.4838
```

```
eig_closed_loop = eig(A - B * K);
disp('Closed-Loop Eigenvalues:');
Closed-Loop Eigenvalues:
disp(eig_closed_loop);
```

```
-1.4060 + 1.3925i
-1.4060 - 1.3925i
-1.3259 + 0.8921i
-1.3259 - 0.8921i
```

LQR TESTING

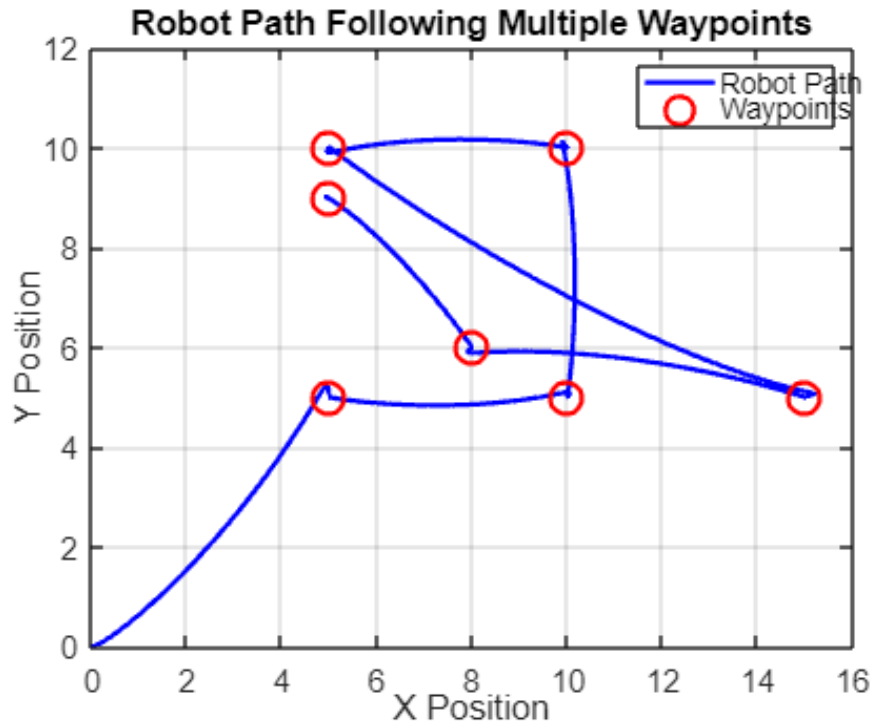


Figure 03: Test output for LQR Controller.

```
% Loop through each waypoint
current_state = initial_state;
for i = 1:size(waypoints, 1)
    target_state = [waypoints(i, 1); waypoints(i, 2); 0; 0]; % Desired
state for each waypoint

    % Simulate the system for the current segment
    [t, states] = ode45(@(t, x) controlled_dynamics(t, x, A, B, K,
target_state), t_span, current_state);

    % Update the current state and store results
    current_state = states(end, :)'; % Update to the last state
    states_all = [states_all; states];
    times_all = [times_all; t + (i-1)*t_span(end)];
end

function dxdt = controlled_dynamics(t, x, A, B, K, target_state)
    u = -K * (x - target_state); % Control law
    dxdt = A * x + B * u;      % Dynamics with control
end
```

EFFECT OF EXTERNAL PARAMETERS

Consider following disturbances:

- Variations in system parameters A and B
$$A_{sim} = A + \Delta A \text{ and } B_{sim} = B + \Delta B$$
- External disturbances in the form of sinusoidal inputs.
$$disturbance = [0; 0; 0.1 \sin(t); 0.05 \cos(t)]$$
- Measurement noise introduced into the state variables.
$$noise = N(0, 0.1^2)$$
- Varying initial condition to a non-zero value.
$$Initial \ state: [x_0, y_0, \theta_0, v_0] = [2, 3, 0.1, 0.8]$$

```
delta_A = 0.1 * rand(size(A)); % Small variation in A
delta_B = 0.1 * rand(size(B)); % Small variation in B
A_sim = A + delta_A;
B_sim = B + delta_B;
```

```
noise_amplitude = 0.1; % Adjust this for stronger noise
```

```
function dxdt = controlled_dynamics(t, x, A, B, K,
target_state, noise_amplitude)
    disturbance = [0; 0; 0.1 * sin(t); 0.05 * cos(t)];
    noise = randn(4, 1) * noise_amplitude;
    u = -K * (x - target_state);
    dxdt = A * x + B * u + disturbance + noise;
end
```

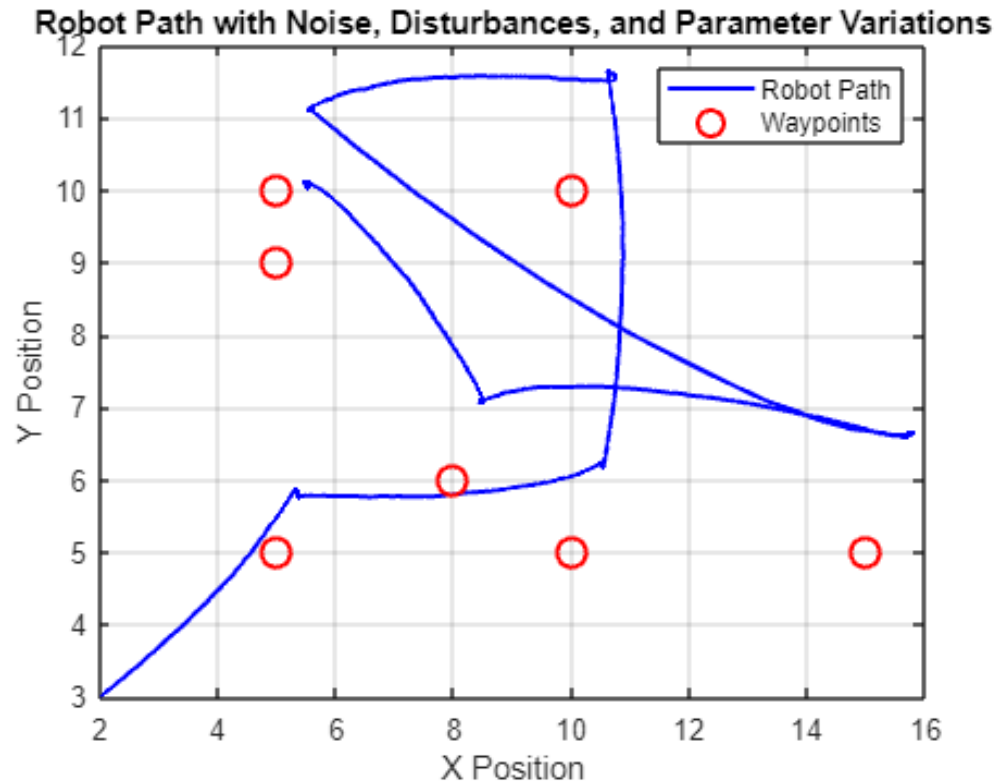



Figure 06: Robot Path correction with Q compensation.

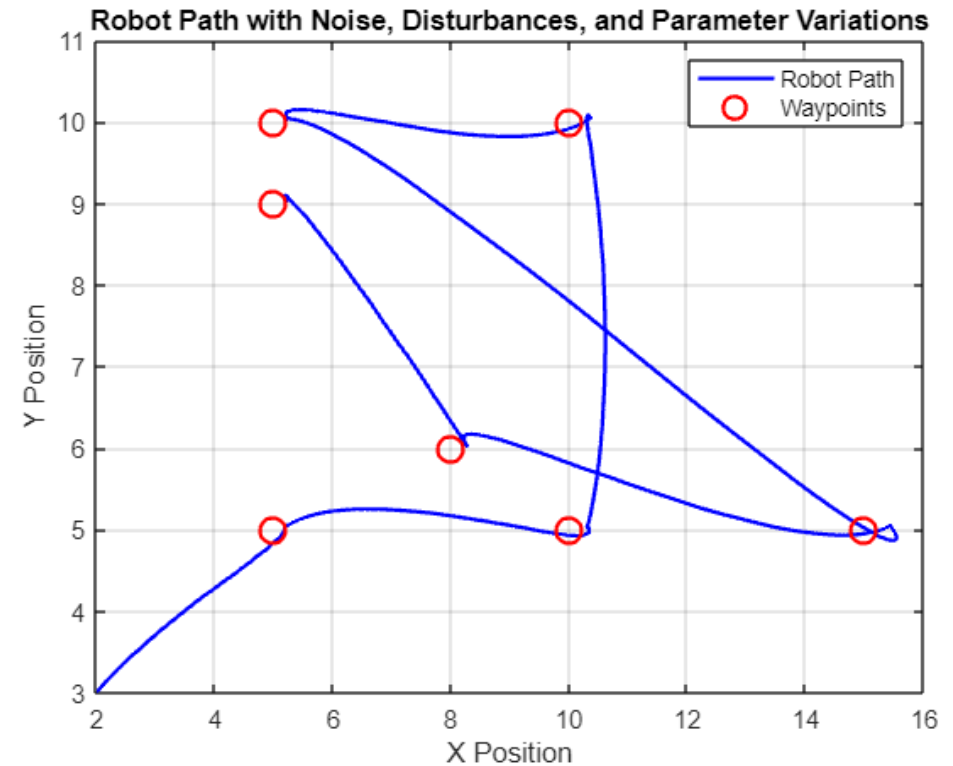


Figure 05: Robot Path deviation due to external parameters.

- The penalizing factor Q was set to $[700, 700, 1, 1]$ by increasing the penalizing factor from 10 to 700 for x and y coordinated the path deviation reduces significantly.
- But in real life implementation increasing Q value is not ideal.
- Hence, different methods like using high precision sensors, feed-forward control, shielding for noise is implemented.

OBSERVER DESIGN

The Observer poles must be placed faster than the controller poles for a quicker response and to ensure the error dynamics $e(t) = x - \hat{x}$ decay rapidly.

Poles from the LQR Design which are

$$-1.4060 \pm 1.3925i \text{ and } -1.3259 \pm 0.8921i$$

The observer time constant (τ) should be smaller than the system dynamics so,

$$\tau = \frac{1}{|\operatorname{Re}(\lambda)|}$$

as highest value negative real pole in controller is -1.4 ,

$$\tau_c \approx \frac{1}{1.4} \approx 0.71 \text{sec}$$

Therefore, $\tau_o < 0.71 \text{sec}$

assuming values which are further from origin: $-5, -6, -7, -8$

$$\text{Hence, } \tau_o \approx \frac{1}{5} = 0.2 \text{sec}$$

which is 3 – 4 times faster than the controller which is ideal for design consideration.

OBSERVER GAIN

The observer gain matrix L is determined using the pole placement

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y})$$

where error dynamics are

$$\dot{e} = (A - LC)e \text{ where } e = x - \hat{x}.$$

The obtained observer gain matrix is as follows:

13.5632	0.7281
1.9386	12.4368
19.6970	38.5752
45.1536	4.7165

```
% Observability check
O = obsv(A, C);
if rank(O) == size(A, 1)
    disp('System is observable. ');
else
    disp('System is not observable. ');
end
System is observable.
% Define desired observer poles
observer_poles = [-5, -6, -7, -8]; % Choose faster poles than
controller
L = place(A', C', observer_poles); % Compute observer gain matrix
disp('Observer Gain Matrix (L): ');
Observer Gain Matrix (L):
disp(L);
13.5632    0.7281
 1.9386   12.4368
19.6970   38.5752
45.1536    4.7165
```

OBSERVER TESTING

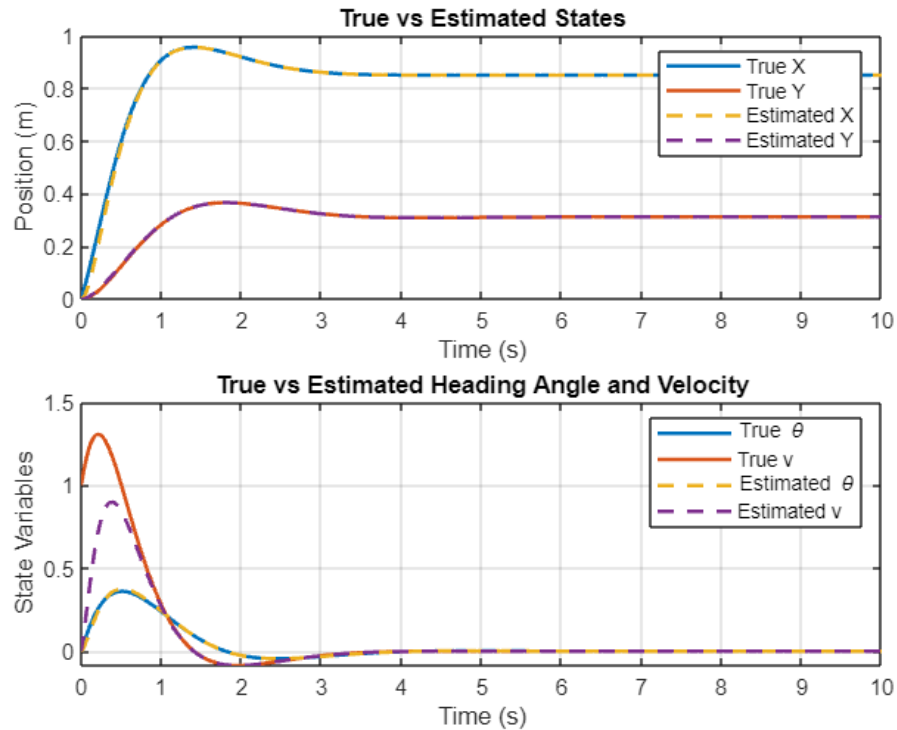


Figure 04: Test output for Observer Design.

```
[t, states] = ode45(@(t, x) system_with_observer(t, x, A, B, C, L,  
K, initial_state), t_span, [initial_state; initial_estimate]);
```

```
% Extract true and estimated states
```

```
true_states = states(:, 1:4);
```

```
estimated_states = states(:, 5:8);
```

```
function dxdt = system_with_observer(t, x, A, B, C, L, K,  
true_state)
```

```
    n = length(true_state); % Number of states
```

```
    x_true = x(1:n); % True states
```

```
    x_hat = x(n+1:end); % Estimated states
```

```
    % Control law
```

```
    u = -K * (x_hat - true_state);
```

```
    % True dynamics
```

```
    dx_true = A * x_true + B * u;
```

```
    % Observer dynamics
```

```
    y = C * x_true; % True output
```

```
    y_hat = C * x_hat; % Estimated output
```

```
    dx_hat = A * x_hat + B * u + L * (y - y_hat);
```

```
    dxdt = [dx_true; dx_hat];
```

```
end
```


FUTURE SCOPE

- **Integration with AI Path Planning:** Combine with AI-based algorithms for dynamic environment navigation.
- **Multi-Robot Coordination:** Extend to collaborative tasks with decentralized control.
- **Adaptive Control:** Enhance robustness to handle larger uncertainties.
- **Hardware Implementation:** Test on physical robots with real-world sensors.
- **Sensor Fusion:** Improve state estimation using LIDAR, IMU, or GPS.
- **Real-World Applications:** Deploy for warehouse automation or delivery systems.

CONCLUSION

- **State Space Representation:** Developed a state space representation for the differential drive robot.
- **System Dynamics:** Determined using MATLAB simulation by varying the velocity of the wheels to understand the robot's motion within the warehouse.
- **Feedback Gain of the system:** Designed gain matrix for the system using pole placement.
- **Controller Design:** Designed a Linear Quadratic Regulator (LQR) for path tracking.
- **Observer Design:** Designed a state observer using pole placement to estimate unmeasured states in real time.
- **Robustness Evaluation:** Tested the system under parameter variations (A and B), external disturbances, and sensor noise.


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THANK YOU

Mukul Bhatia | Sajin Shrestha | Vighnesh Deolika



Q & A