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A Reinforcement Learning Model for Autonomous Agent Navigation in Shared Spaces

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Overview

- Emergence of self-driving agents
- Shared spaces
- Navigation systems and models
- Conclusion

Emergence of AVs

- Advancements in IoT leads to smart city development.
- Waymo taxis and Tesla cars
- Autonomous trolleys and mobile lockers
- The challenge of managing the mixed transportation



Shift in Urban Street Design

- Streets can be more of a place, rather than a link
- The "streets for shared spaces" program in New South Wales in 2020
- Transform streets into shared space to make them more inclusive and vibrant urban areas



Old Christchurch Road (UK), Before and After implementation of the shared space design (ref: Evaluation and implementation of Shared Spaces report in NSW 2022).

Shared Environment's Features

- Mixed users
- No traditional traffic demarcations
- Homogenous surface
- Low speed limits
- Informal right of way
- Landscaping and street furniture
- High densely populated
- Stochastic dynamic movements



Autostradas in ports.
Ref: industrysearch.com.au



Location: Detroit, Michigan.
ref: livinglabdetroit.com/portfolio/bagley-shared-street-design/

Self-driving Cars Navigation Methods

- Physics-based models
- Learning-based models



Comparison between the Models

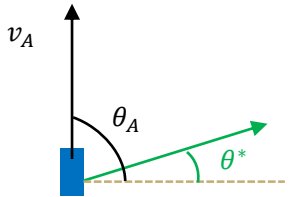
PHYSICS-BASED

- Based on equations
- Requires manual adjustments
- Require less data to develop
- Computationally efficient
- Cannot capture intricated human behaviours
- Deterministic
- Reliable outputs
- Can ensure safety

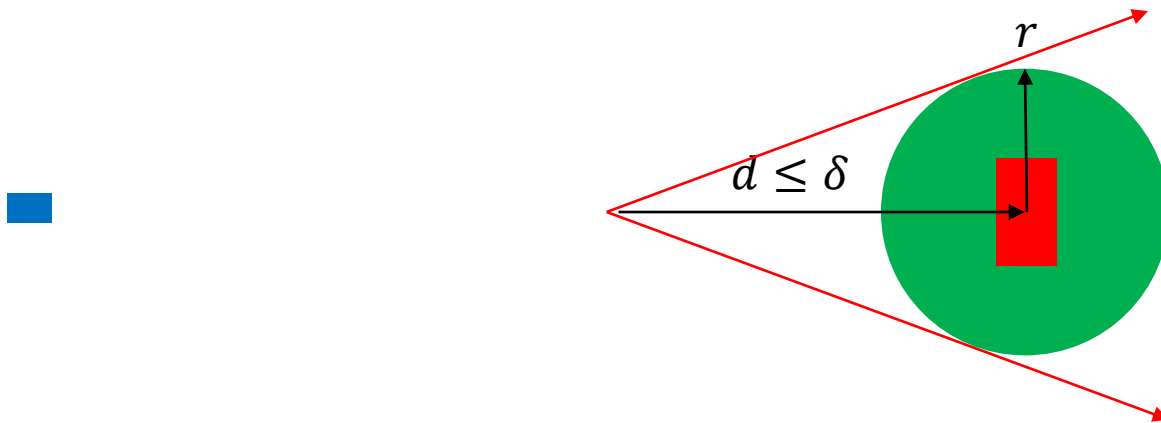
LEARNING-BASED

- Learn through interactions
- Adaptable to stochastic conditions
- Can handle uncertainty
- Require a significant amount of data.
- Captures complex behaviors
- Computationally expensive
- Can imitate human behaviour
- Outputs could be unreliable or unrealistic

Agent Features



How to Avoid an Obstacle?



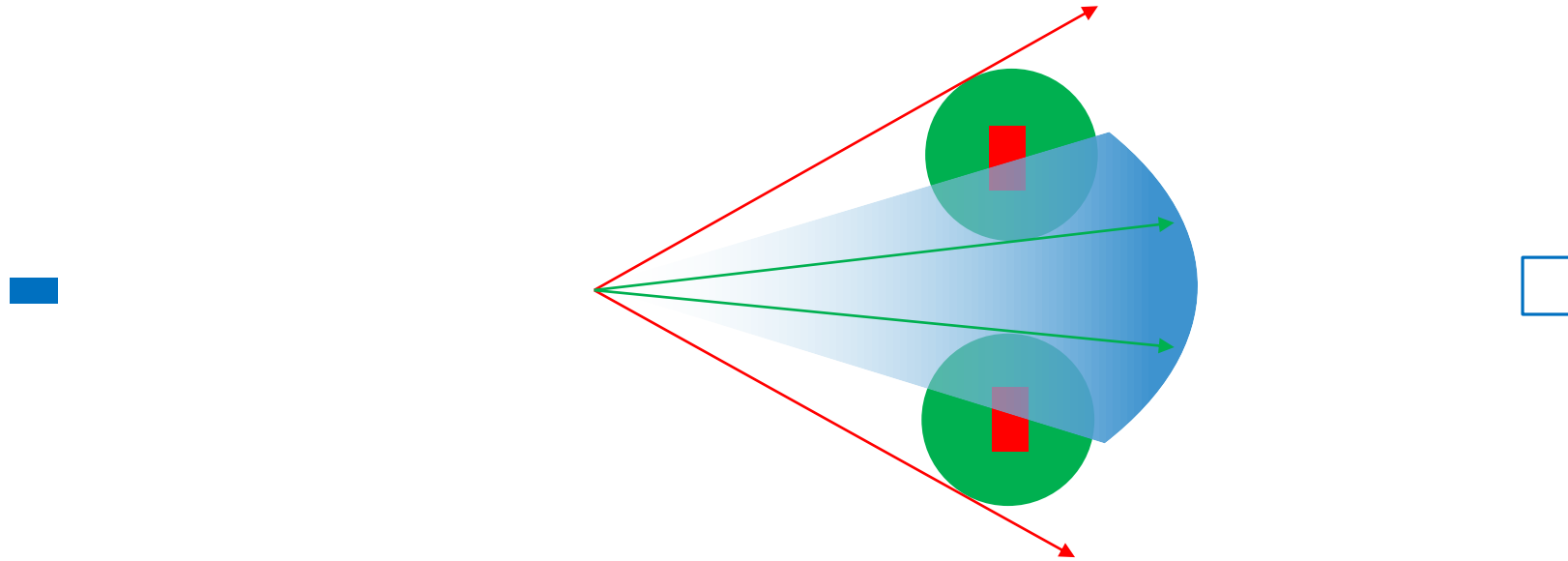
d : Distance to the obstacle.

δ : Agent sensor range.

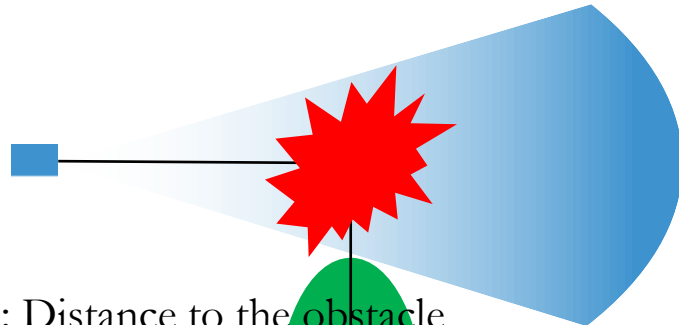
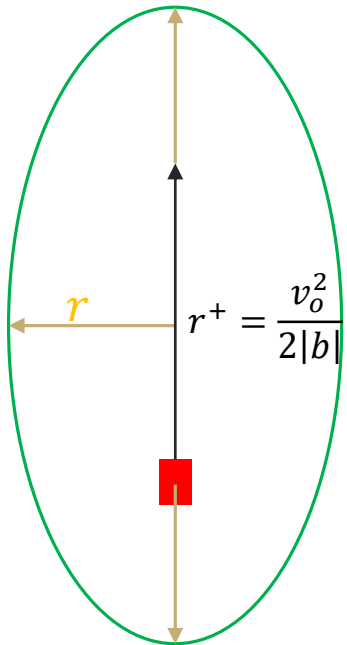
r : Minimum safe distance from obstacle.



Energy minimization



Avoid the Moving Obstacles



- d : Distance to the obstacle
- r : Minimum safe distance from obstacle
- r^+ : The extra length added to the axis
- b : The comfort braking deceleration

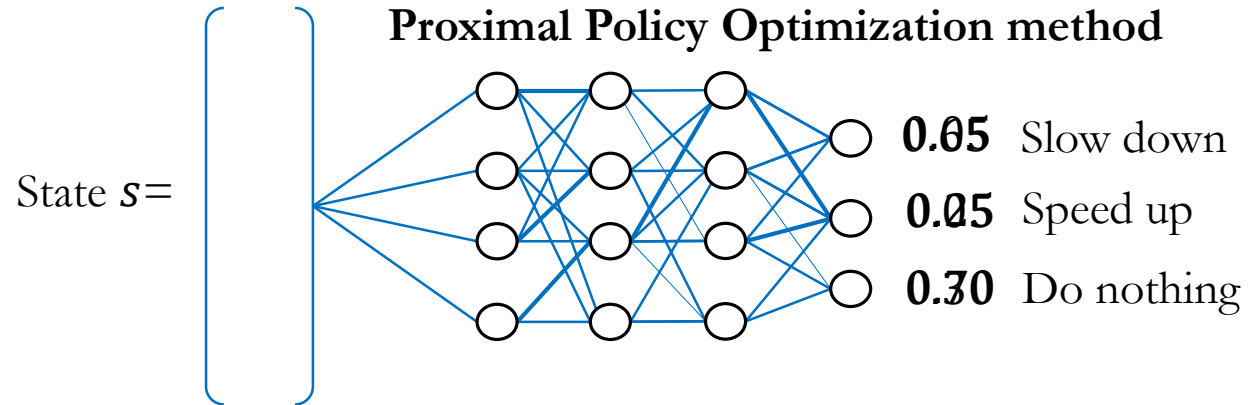
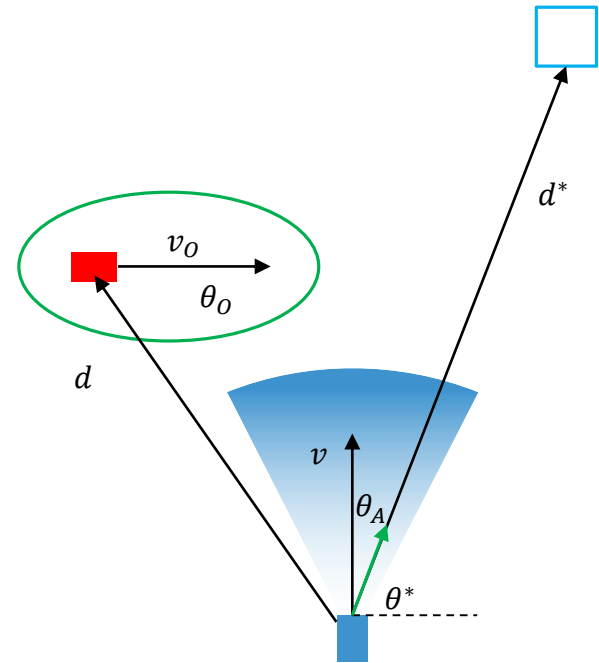
v_A : The agent velocity

v_o : The obstacle velocity

Agent braking deceleration: $\left(-\frac{v_A^2}{2d}\right)$



Learning Process



$$\text{Reward} = -(\text{Euclidean distance to the goal state}) + \ln(\text{distance to the nearest obstacle})$$

An efficient learning process needs step-by-step training

Simulation result: Agent's navigation

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state of the goal
state of the goal

ndom_integers(10, area, num_objects).tolist()
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om.random_integers(10, area, num_objects).tolist()
om.random_integers(10, area, num_objects).tolist()
m.uniform(0, 2 * np.pi, num_objects).tolist()
    in range(num_objects)]

, 0, 100, 100]
0, 0, 100, 30]
0, 100, 50, 0, 0]
0, 50, 50, 20, 80]
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cts_y)

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Simulation result: Trajectory of agents

```
x_new, y_new = length, "v= %s" % (np.round(v, 1)), color='r')
objects_goal_x[ind], objects_goal_y[ind], 's', markersize=20, color=colors[ind])

ax(x_edge[1], x_edge[0] + 10))
ax(y_edge[1], y_edge[0] + 10))
time: {frame} seconds') # Display the frame number as the title

nd position index

os_index + 1) % len(x_history[0])
# Cycle through actions

(x_history)):
angle((objects_goal_x[ind] - length, objects_goal_y[ind] - length), 2 * length,
      2 * length, linewidth=1, edgecolor=colors[ind], facecolor='None')
t)

n(decomposed_x[i] for i in range(len(x_history)))
# Adjust as needed

on with the specified interval
fig, update, frames=num_frames, repeat=False, interval=animation_speed)
m)")
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Future Directions



Combined approaches



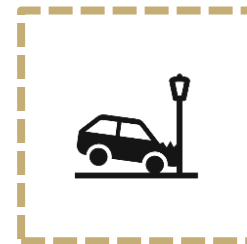
Energy minimization



Correct the mistakes



Socially acceptable behavior



Motion prediction



Real test



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Thank You!



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