

16.32 Final Report: Dynamic Programming for Car Kinematics

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Abstract—A dynamic programming scheme was implemented in Python to solve the optimal car motion problem. The Reeds-Shepp Car model was used over a state space $X \subset x \times y \times \theta$, with inputs $U \subset v \times \phi$. A simple collision checking algorithm was incorporated into the dynamic programming solver to allow for the placement of arbitrary rectangular obstacles in the state space. The solver was run over multiple demonstrative scenarios, including parallel parking, navigation around an obstacle, and a 180 degree turn. The algorithm runs in $O(e^n)$, where n is the number of state space and input variables, in this case 5. Even taking advantage of a few heuristic tricks, this borders on the edge of feasibility due to the curse of dimensionality. Future work might involve more computationally efficient approximate solutions to the optimization problem, including RRTs.

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1. BACKGROUND

[1]

Dynamic Programming

Dynamic programming provides a numerical tool for approximating optimization problems. Specifically, dynamic programming is the discrete-time approximation of the Hamilton-Jacobi-Bellman equation

$$-J_t^* = \min_{u \in U} \mathcal{H}$$

and in the limit provides the exact solution for the optimal cost-to-go, J^* . By discretizing input actions and state, one effectively creates a mesh of state variables over which the combination of discretized state variables may be applied. [2]

Algorithm

The dynamic programming implementation is based off of that given by

2. METHOD

The Reeds-Shepp Car

Collision Checking

```

1: procedure DYNAMIC PROGRAMMING( $X, U$ )
2:    $r \leftarrow a \bmod b$ 
3:   while  $r \neq 0$  do           ▷ We have the answer if r is 0
4:      $a \leftarrow b$ 
5:      $b \leftarrow r$ 
6:      $r \leftarrow a \bmod b$ 
7:   end while
8:   return  $b$                  ▷ The gcd is b
9: end procedure

```

Figure 1. Simple Collision Checking

Dynamic Programming

```

1: procedure DYNAMIC PROGRAMMING( $X, U$ )
2:    $J^* \leftarrow h(x(t_f))$      ▷ For admissible final position
3:   for  $k$  iterations do       ▷  $k$  mesh iterations
4:     for  $X$  states do         ▷ discretized state
5:       for  $U$  inputs do       ▷ discretized inputs
6:          $x_{k+1} \leftarrow f(x_k, u_k)$ 
7:          $b \leftarrow r$ 
8:          $r \leftarrow a \bmod b$ 
9:       end for
10:    end for
11:  end for
12:  return  $b$                  ▷ The gcd is b
13: end procedure

```

Figure 2. Computational Dynamic Programming

Implementation

```

1: procedure EUCLID( $a, b$ )       ▷ The g.c.d. of a and b
2:    $r \leftarrow a \bmod b$ 
3:   while  $r \neq 0$  do         ▷ We have the answer if r is 0
4:      $a \leftarrow b$ 
5:      $b \leftarrow r$ 
6:      $r \leftarrow a \bmod b$ 
7:   end while
8:   return  $b$                  ▷ The gcd is b
9: end procedure

```

Figure 3. Interpolation Logic

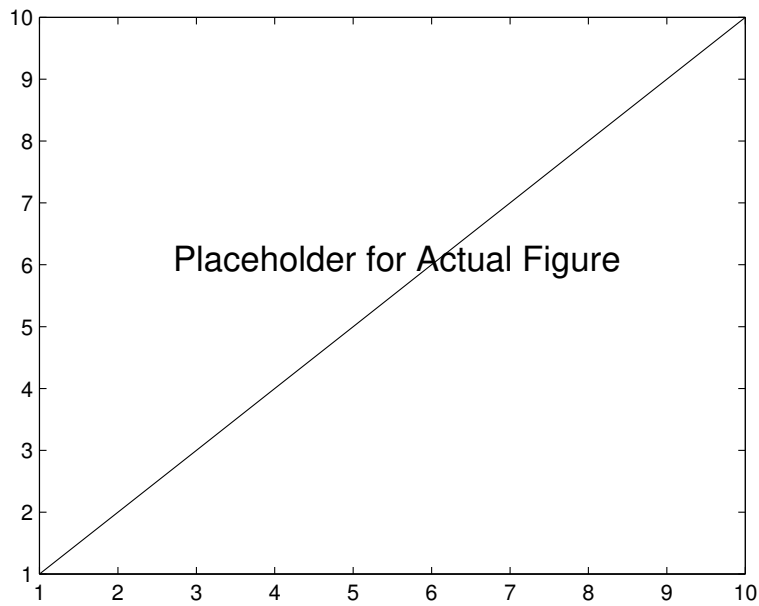


Figure 4. Here is an example of a figure that spans both columns.

3. RESULTS

Computational Complexity

Sample Scenarios

4. CONCLUSIONS

Discussion

Conclusion

APPENDICES

A. DYNAMIC PROGRAMMING ALGORITHM

[3]

ACKNOWLEDGMENTS

I would like to thank Professor Hall for teaching what was a challenging, but very interesting course.

REFERENCES

- [1] S. LaValle, "Randomized Kinodynamic Planning," 2001.
- [2] S. Hall, "Lecture 9: HJB Equation," pp. 1–32, 2018.
- [3] Kirk, "Optimal control theory," pp. 1018–1018, 1971. [Online]. Available: <http://doi.wiley.com/10.1002/aic.690170452>

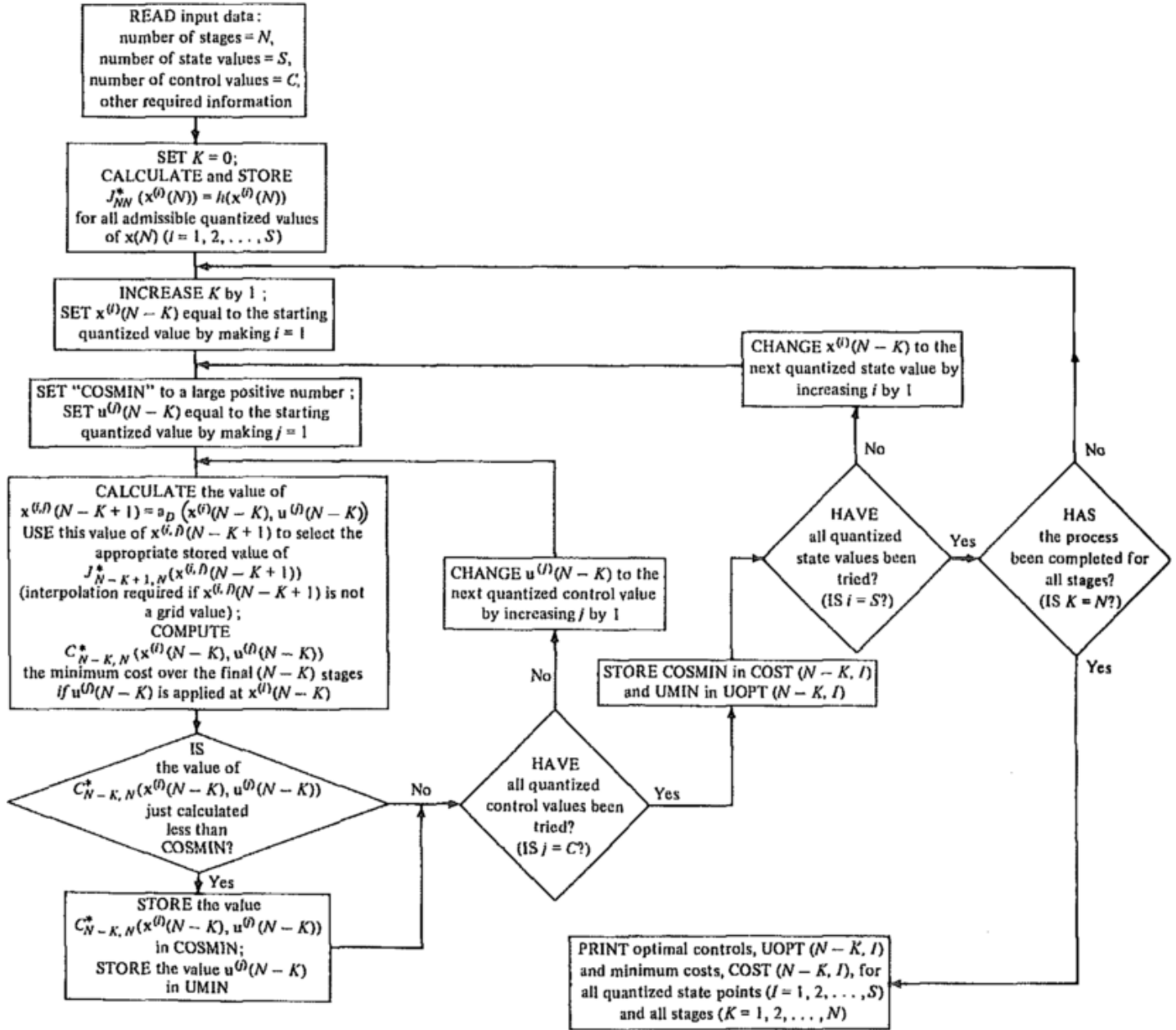


Figure 5. The general dynamic programming algorithm.