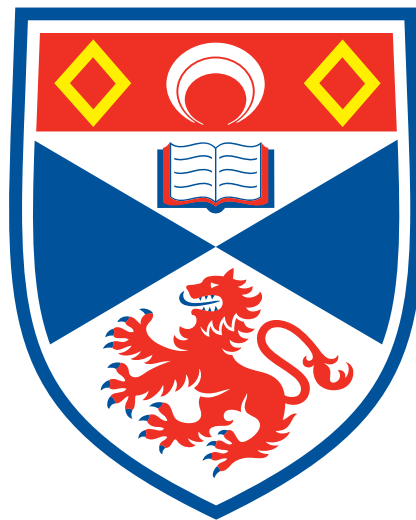

Generating Safe Trajectories in Stochastic Dynamic Enviroments



University of
St Andrews

CS4099: MAJOR SOFTWARE PROJECT

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Abstract

I declare that the material submitted for assessment is my own work except where credit is explicitly given to others by citation or acknowledgement. This work was performed during the current academic year except where otherwise stated.

The main text of this project report is NNN words long, including project specification and plan.

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Chapter 1

Introduction

Chapter 2

Context Survey

Chapter 3

Ethics

Chapter 4

Software Development Framework

Chapter 5

Objectives

$$J(C) = \int_C \exp \left(P_A(x, y, t_0, t_m) \right) ds \quad (5.1)$$

Chapter 6

Planner Methodology

6.1 Potential Fields

6.2 Space-time Roadmap

6.3 Probabilistic Roadmap With Best First Search

Chapter 7

Design

7.1 Agents

$$P_a(x, y, t_0, t_m) = \int_{t_0}^{t_m} \mathcal{N}(\zeta_a(t), \alpha \cdot (t - t_0)^2 + \beta, x, y) \cdot (t_m - t)^\gamma dt \quad (7.1)$$

Where $\mathcal{N}(\mu, \sigma^2, x, y)$ is the evaluation of a 3D normal distribution centered at (μ_x, μ_y) with a variance of σ^2 at (x, y) .

$$P_A(x, y, t_0, t_m) = \frac{\sum_{a \in A} P_a(x, y, t_0, t_m)}{|A|} \quad (7.2)$$

$$\zeta_a(t) = \begin{cases} I_a + \int_{T_a}^t \dot{\zeta}_a(\lambda) d\lambda & \text{if } t \geq T_a \\ \tilde{\zeta}_a(t) & \text{if } t < T_a \end{cases} \quad (7.3)$$

$$\tilde{\zeta}_a(t) = I_a^{(0)} + \int_0^t \dot{\zeta}_a(\lambda) + \rho d\lambda \quad (7.4)$$

7.2 Planning Algorithm

$$C_A(i, j) = \int_0^1 \exp \left(P_A(x(\lambda), y(\lambda), i_t, j_t) + 1 \right) \cdot \|i - j\|_2 d\lambda \quad (7.5)$$

Where $x(\lambda) = (j_x - i_x) \cdot \lambda + i_x$ and $y(\lambda) = (j_y - i_y) \cdot \lambda + i_y$ are the parametric equations of the line from i to j .

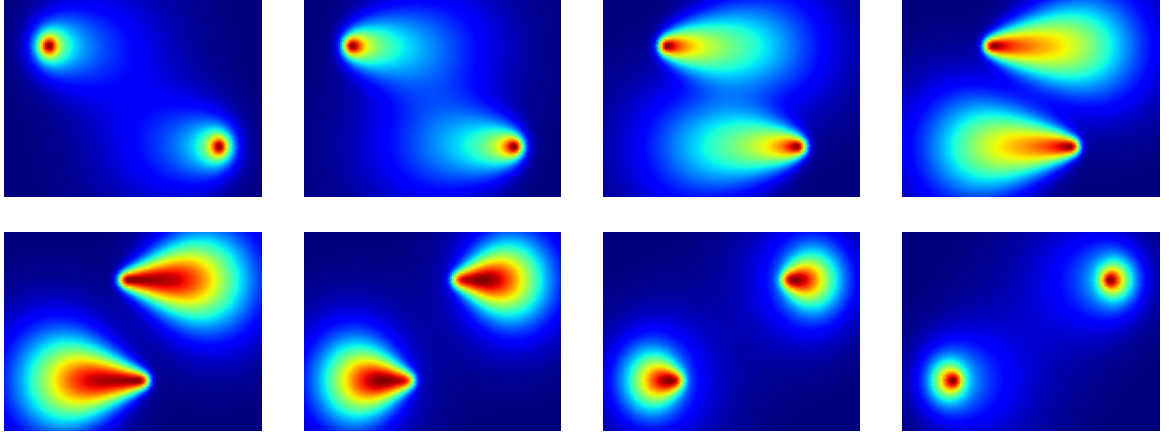


Figure 7.1: Cost distributions indicating the likelihood that an agent will be at a certain location within a given time interval. These figures show how this distribution changes over time (left to right, top to bottom)

Algorithm 1 ROADMAP(n, d, w, h, O)

Input:

n : Maximum number of samples
 d : Maximum distance between neighbouring nodes
 O : Set of obstacles

Output:

An unweighted graph of points describing the connectivity of the environment

```

1: for  $i = 1$  to  $n$  do
2:    $q \leftarrow \text{RANDOMPOINT2D}(w, h)$ 
3:   if  $\bigwedge_{o \in O} \neg \text{COLLISION}(o, q)$  then
4:      $V \leftarrow V \cup \{q\}$ 
5:   for all  $q_i \in V$  do
6:     for all  $q_j \in V$  do
7:       if  $q_i \neq q_j \wedge \|q_i - q_j\| \leq d$  then
8:          $E \leftarrow E \cup \{(q_i, q_j)\}$ 
9: return  $(V, E)$ 
    
```

Algorithm 2 GETPATH($n, d, w, h, \delta, p, g, O, A, R$)

Input:

n : Maximum number of samples for the roadmap
 d : Maximum distance between neighbouring nodes in the roadmap
 w : Width of the scene
 h : Height of the scene

Output:

```

1:  $(V, E) \leftarrow \text{ROADMAP}(n, d, w, h, O)$ 
2:  $\Pi \leftarrow \emptyset$ 
3:  $q \leftarrow p$ 
4: while  $\|\text{BACK}(\Pi) - g\|_2 > R$  do
5:    $\pi \leftarrow \text{SEARCHGRAPH}(V, E, R, A, q, g)$ 
6:   for all  $i \in \pi$  do
7:      $\Pi \leftarrow \Pi \cup \{i\}$ 
8:     for all  $a \in A$  do
9:        $\text{STEP}(a)$ 
10:    if  $\bigvee_{a \in A} \|\tilde{\zeta}_a(i_t) - \zeta_a(i_t)\| > \delta$  then
11:      for all  $a \in A$  do
12:         $\text{UPDATE}(\zeta_a, \tilde{\zeta}_a)$ 
13:       $q \leftarrow i$ 
14:      break
15: return  $\Pi$ 

```

Algorithm 3 SEARCHGRAPH(V, E, R, A, p, g)

```

1:  $Q \leftarrow \text{PRIORITYQUEUE}()$ 
2:  $D \leftarrow \text{DICTIONARY}()$ 
3:  $\Pi \leftarrow \text{DICTIONARY}()$ 
4:  $\text{INSERT}(Q, p, 0)$ 
5: while  $\neg \text{EMPTY}(Q)$  do
6:    $q, w \leftarrow \text{POP}(Q)$ 
7:   if  $\|q - g\|_2 \leq R$  then
8:     return  $\text{BACKTRACKPATH}(p, g, \Pi)$ 
9:    $N \leftarrow \text{GETTEMPORALNEIGHBOURS}(V, E, q)$ 
10:  for all  $n \in N$  do
11:     $\Pi_n \leftarrow q$ 
12:     $c \leftarrow \psi \cdot C_A(q, n) + \omega \cdot D_n$ 
13:     $D_n \leftarrow D_n + 1$ 
14:     $Q \leftarrow \text{INSERT}(Q, n, c)$ 

```

Algorithm 4 GETTEMPORALNEIGHBOURS(V, E, q)

```

1:  $S \leftarrow \emptyset$ 
2:  $N \leftarrow \text{NEIGHBOURS}(V, E, q)$ 
3: for all  $n \in N$  do
4:    $t \leftarrow \|q - n\|_2 / s + q_t$ 
5:    $S \leftarrow S \cup \{(n_x, n_y, t)\}$ 

```

Algorithm 5 BACKTRACKPATH(p, g, Π)

```

1:  $q \leftarrow g$ 
2:  $S \leftarrow \text{STACK}()$ 
3: while  $\Pi_q \neq p$  do
4:    $S \leftarrow \text{PUSH}(S, q)$ 
5:    $q \leftarrow \Pi_q$ 
6:  $S \leftarrow \text{PUSH}(S, p)$ 
7: return  $S$ 

```

Chapter 8

Implementation

Chapter 9

Experimental Setup

Algorithm 6 $\text{PF}(q, g, O, A, R)$

```
1:  $q_{min} \leftarrow q$ 
2:  $p_{min} \leftarrow \infty$ 
3:  $\theta \leftarrow 0$ 
4: while  $\theta \leq 2\pi$  do
5:    $q' \leftarrow q + \delta t \cdot s \cdot \text{ROT}(\theta)$ 
6:    $p \leftarrow U_{\text{rep}}(q', O \cup A) + U_{\text{att}}(q', g)$ 
7:   if  $p < p_{min}$  then
8:      $p_{min} \leftarrow p$ 
9:      $q_{min} \leftarrow q'$ 
10:   $\theta \leftarrow \theta + \delta\theta$ 
11: if  $\|q_{min} - g\| < R$  then
12:   return  $\{p_{min}\}$ 
13: return  $\{q_{min}\} \cup \text{PF}(q_{min}, g, O, R)$ 
```

9.1 Metrics

$$\text{MinDist}(\Pi) = \min_{t \in \mathcal{T}} \min_{a \in A} \|\zeta_a(t) - \Pi(t)\| \quad (9.1)$$

$$\text{MaxCost}(\Pi) = \max_{t \in \mathcal{T}} P_A(\Pi(t)) \quad (9.2)$$

$$\text{AvgCost}(\Pi) = \int_{\mathcal{T}} P_A(\Pi(t)) \, dt \quad (9.3)$$

Chapter 10

Results

10.1 Safety

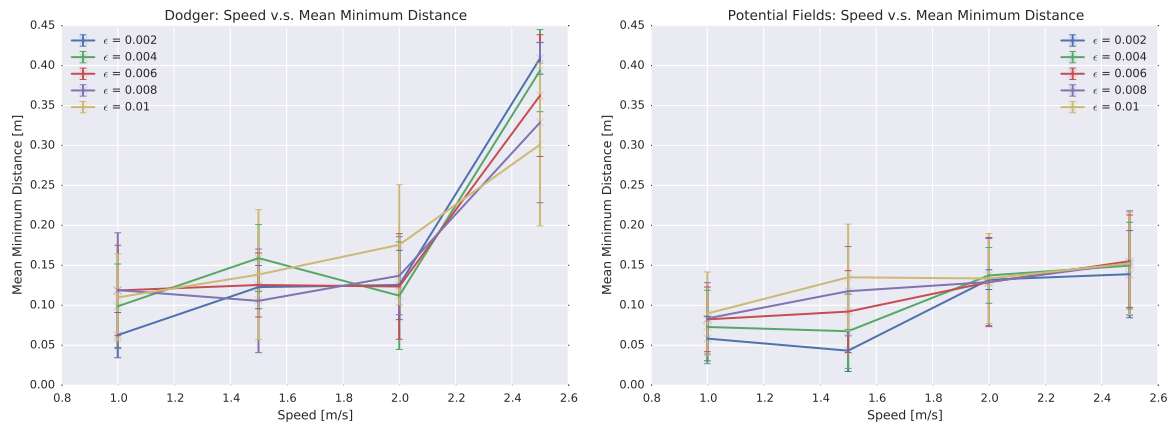


Figure 10.1: Plots showing how the average minimum distance to the obstacles changes as the speed increases for various amounts of obstacle position uncertainties

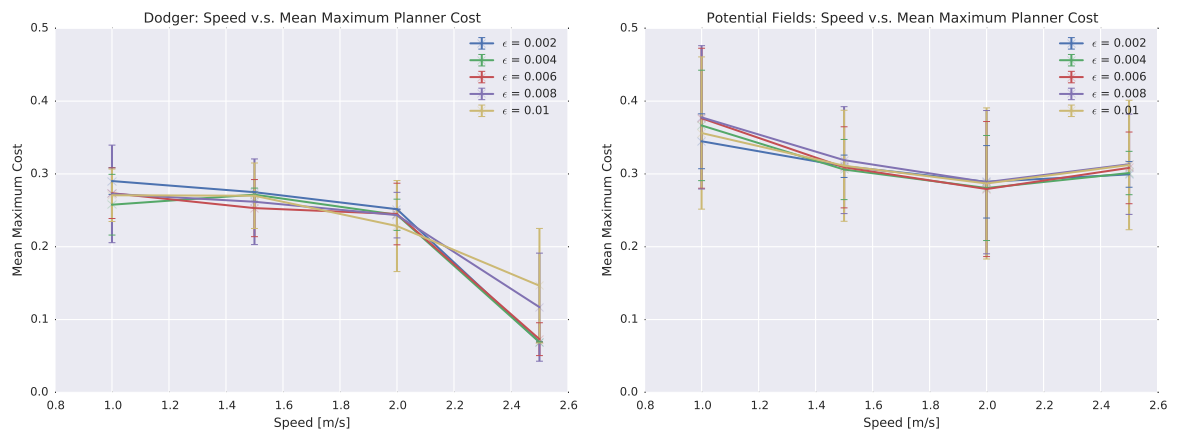


Figure 10.2:

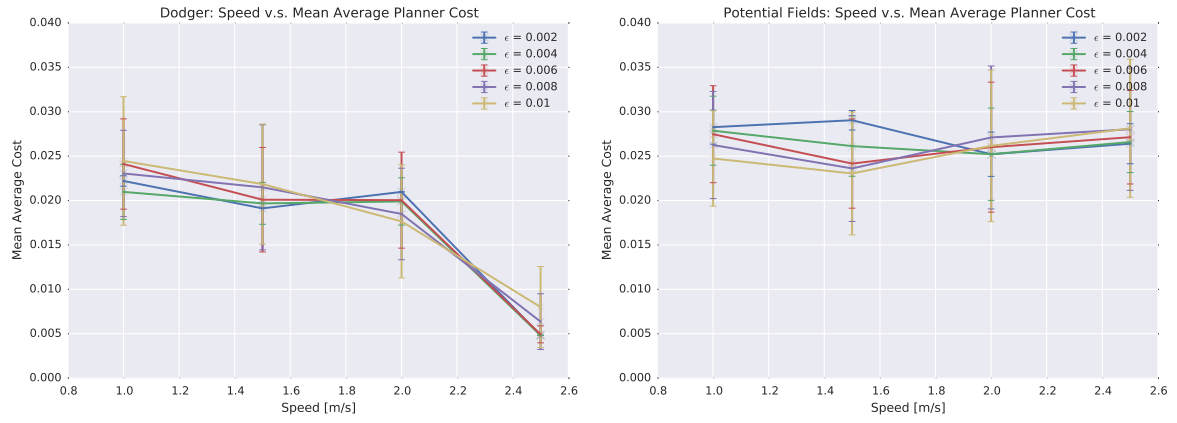


Figure 10.3:

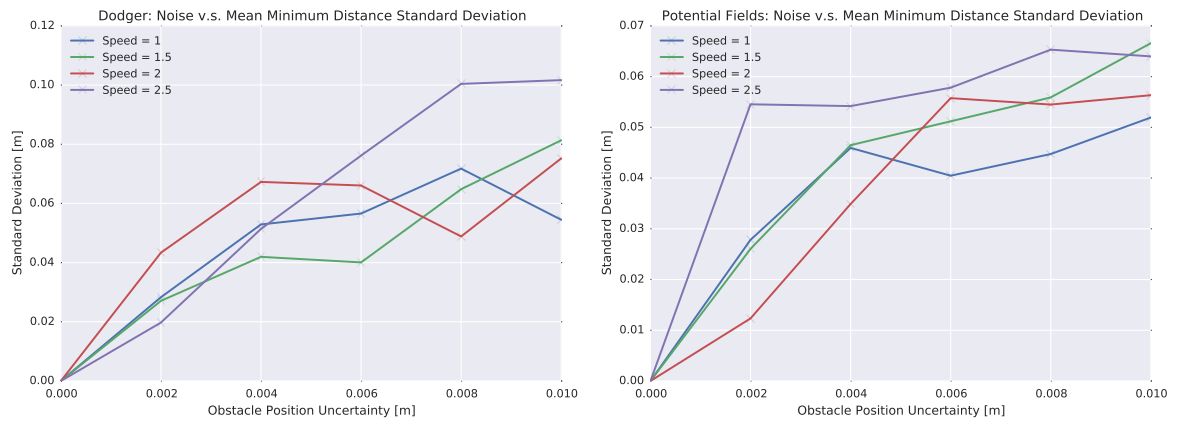


Figure 10.4:

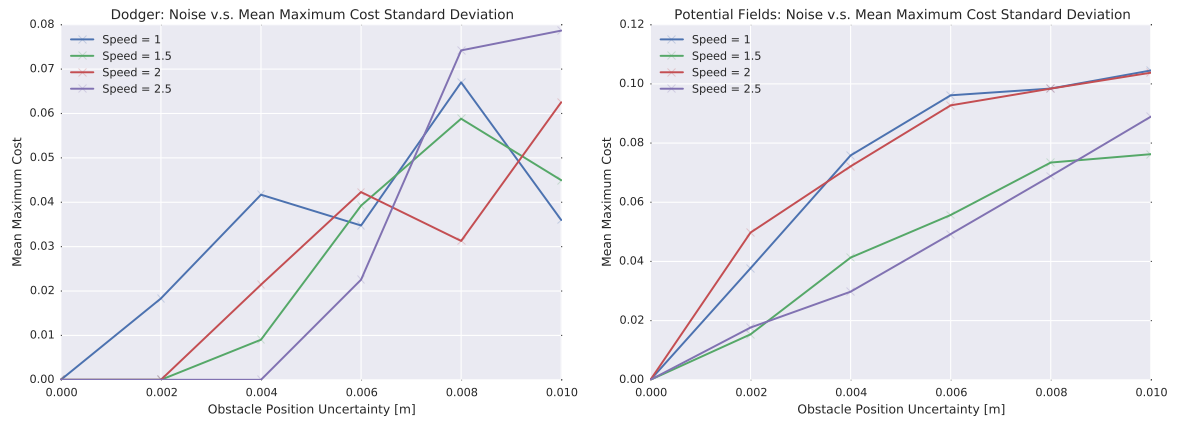


Figure 10.5:

10.1.1 Variance

10.2 Computational Time

10.2.1 Variance

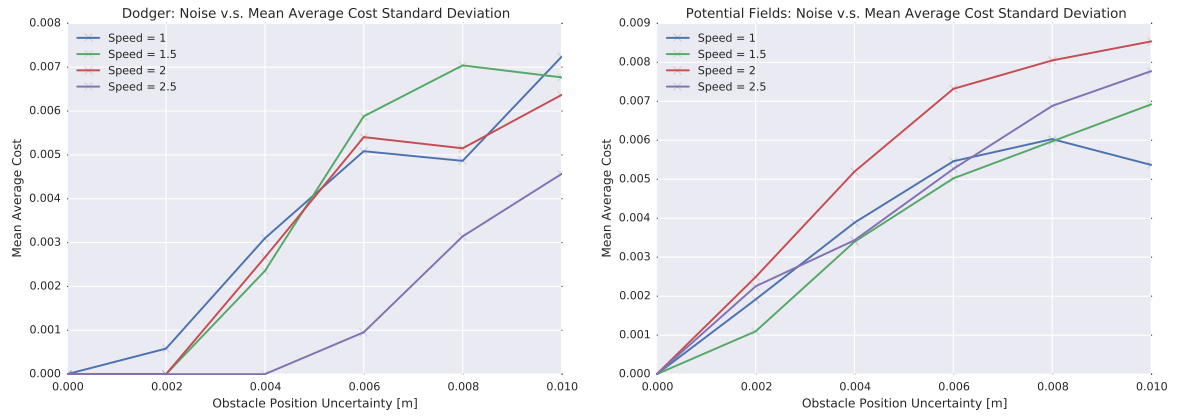


Figure 10.6:

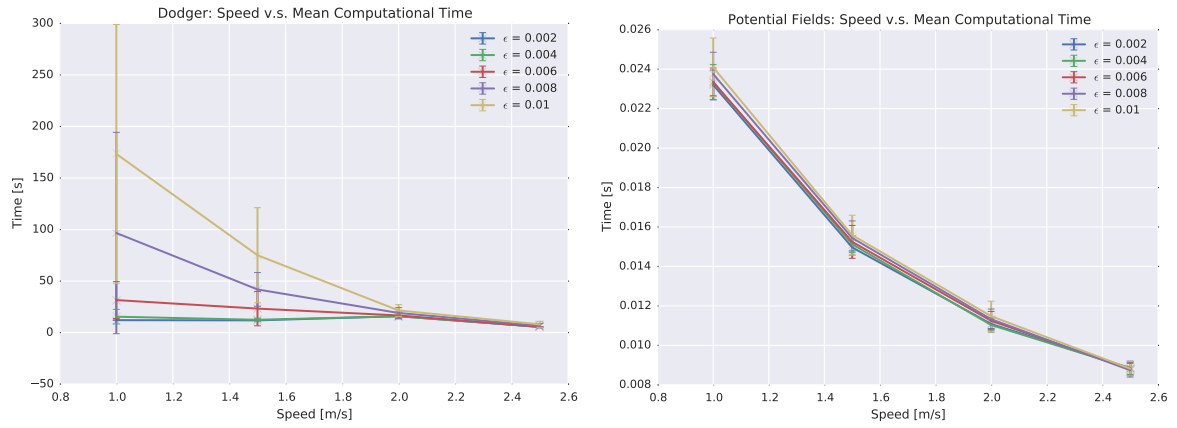


Figure 10.7: Plots showing how the computational time changes as the speed increases for various amounts of obstacle position uncertainties

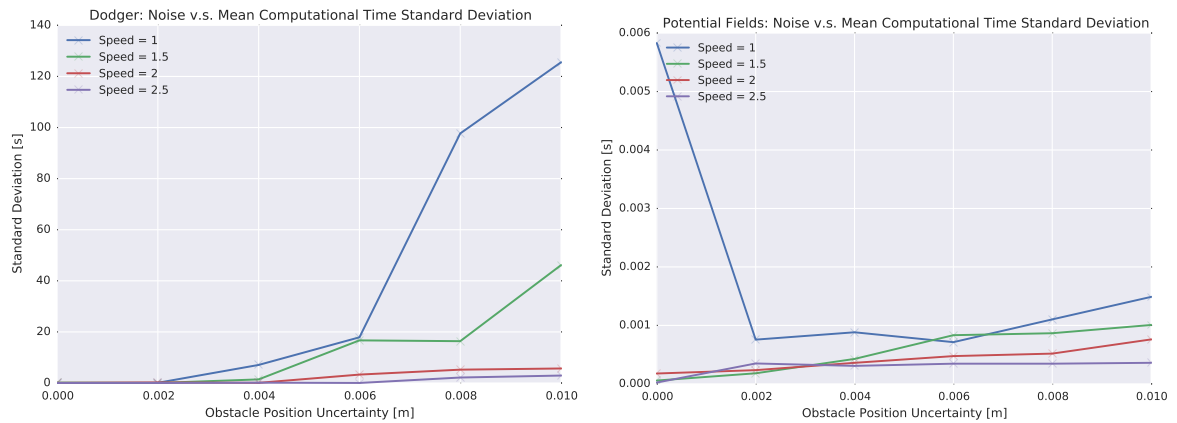


Figure 10.8:

Chapter 11

Discussion

Chapter 12

Acknowledgements