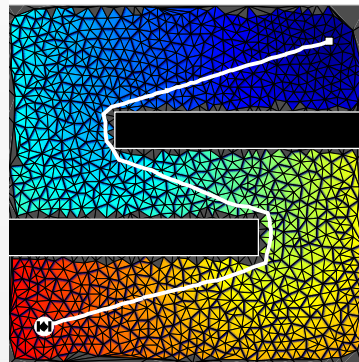
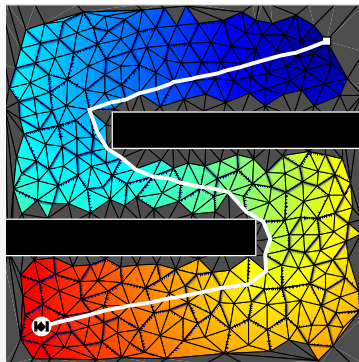
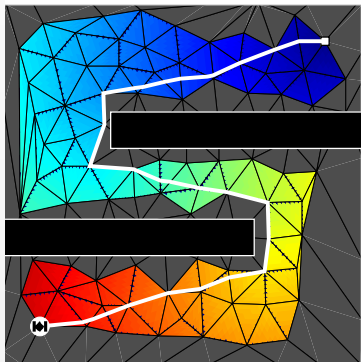


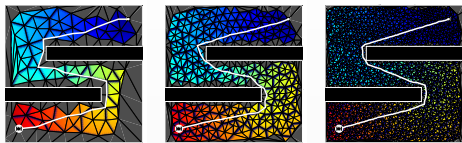
# Sampling-based Volumetric Methods for Optimal Feedback Planning

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Massachusetts Institute of Technology



## General Idea




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### Algorithm 1 ACIDIC

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**Input:** Sets  $X_{\text{goal}} \subseteq X_{\text{free}} \subseteq X$

```

1: loop
2:    $x_{\text{new}} \leftarrow \text{SamplePoint}(X)$ 
3:    $\text{UpdateDelaunay}(x_{\text{new}})$ 
4:   for all  $\tau_{\text{new}}$  do
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6:    $\text{ReplanFMM}(x_{\text{new}})$ 
7:   yield feedback  $\pi(x)$ 

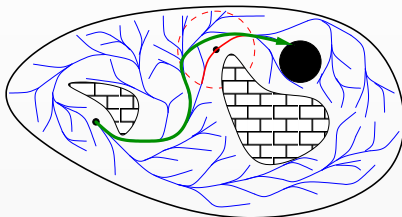
```

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- Random and pseudo-random sampling
- Volumetric free-space approximation
- Feedback policy computations
- Asymptotic convergence

## Motivation

### Path-centric algorithms



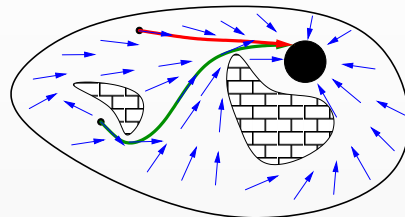
#### Pros

We are using graphs for planning algorithms because many efficient graph libraries are available

#### Cons

The main problem with graphs is in artificial restriction of robot movements on a set of zero measure

### Policy-centric algorithms



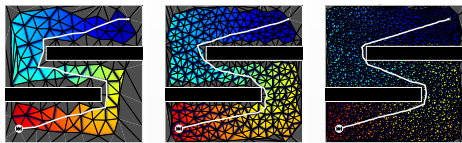
#### Pros

A feedback policy stabilizes robot motions towards the goal without using path-following controller middleware

#### Cons

Numerical methods for feedback function computations are currently unavailable, but we are determined to eliminate this problem

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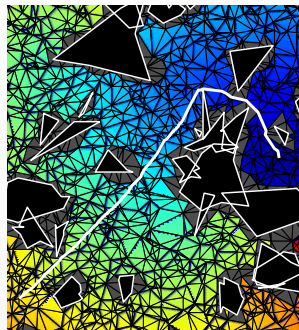
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## Sampling Strategies

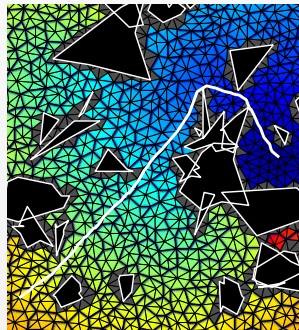
### Random Sampling

- Random sampling avoids unfortunate subspace alignment
- Random sampling **does not** avoid the curse of dimensionality
- Finding narrow corridors using random sampling is as hard as using regular grids [LaValle, Branicky, Lindemann, 2004]

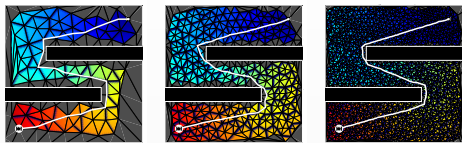


### Delaunay Refinement [Ruppert, 1995; Shewchuk, 2010]

- Insert next sample at the center of the largest circumsphere
- Optimal dispersion convergence
- Randomly seeded deterministic sampling algorithm
- Sampling bias towards *regions of interest*



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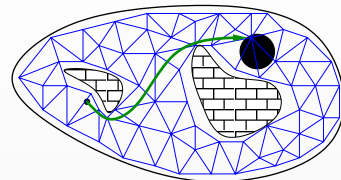
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## Incremental Delaunay Triangulation

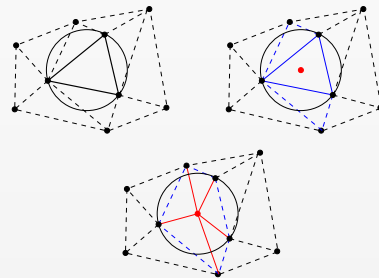
### Delaunay Triangulation

- Delaunay triangulation of a sample set is a geometric simplicial complex such that the interior of all simplex circumspheres do not contain any sampled points
- The complexity of Delaunay triangulation is  $O(N)$  for  $N$  samples in the *general position*, regardless of the dimension number  $d$  [Miles, 1974]

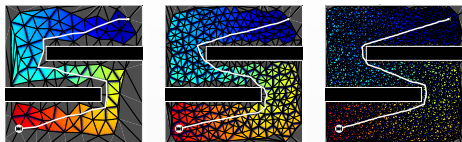


### Incremental Delaunay Triangulation

- Start with the initial Delaunay triangulation
- Newly inserted sample always violates empty-circumsphere property
- “Rewire” local simplices to enforce this property
- Computational complexity  $O(\log(N))$  ( $N$  is the size of the initial sample set)



## General Idea




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### Algorithm 1 ACIDIC

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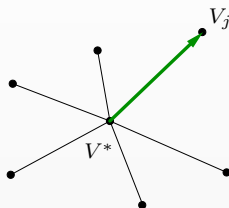
- 1: **loop**
  - 2:  $x_{\text{new}} \leftarrow \text{SamplePoint}(X)$
  - 3:  $\text{UpdateDelaunay}(x_{\text{new}})$
  - 4: **for all**  $\tau_{\text{new}}$  **do**
  - 5:      $\text{CollisionCheck}(\tau_{\text{new}})$
  - 6: **ReplanFMM}(x\_{\text{new}})**
  - 7: **yield** feedback  $\pi(x)$
- 

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## Repairing Fast Marching Method

### Dijkstra's Algorithm

[Dijkstra, 1959]



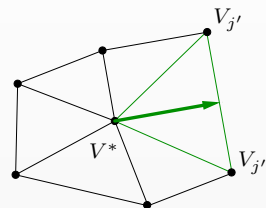
- 1: Initialize  $Q$
- 2: **while**  $Q$  is not empty **do**
- 3:   Pop  $j$  with least  $V_j$  from  $Q$
- 4:   **for all**  $i \in \mathcal{N}(j)$  **do**
- 5:      $V^* \leftarrow \|x_i - x_j\| + V_j$
- 6:     **if**  $V^* < V_i$  **then**
- 7:       Update  $V_i$

#### Is it difficult?

Change one line in your favorite graph-search algorithm: Dijkstra, A\*, D\*, LPA\*, ARA\*, etc\*

### Fast Marching Method

[Sethian, 1999]

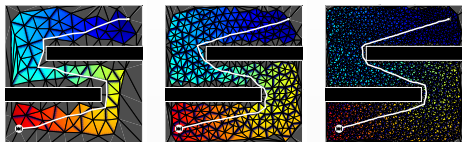


- 1: Initialize  $Q$
- 2: **while**  $Q$  is not empty **do**
- 3:   Pop  $j$  with least  $V_j$  from  $Q$
- 4:   **for all**  $i \in T \in \mathcal{N}(j)$  **do**
- 5:      $V^* \leftarrow \text{minloc}(i, T, V)$
- 6:     **if**  $V^* < V_i$  **then**
- 7:       Update  $V_i$

#### What is necessary?

Use your favorite interpolation method to propagate cost-to-go function values

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## Convergence Rate and Computational Complexity

### Convergence Rate

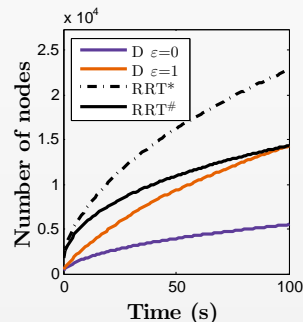
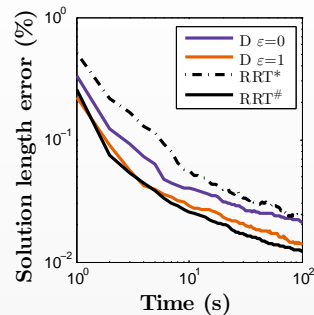
Deterministic sampling	$\mathcal{E} \sim O\left(\left(\frac{1}{N}\right)^{\frac{1}{d}}\right)$
Random sampling	$\mathcal{E} \sim O\left(\left(\frac{\log N}{N}\right)^{\frac{1}{d}}\right)$
Delaunay refinement	$\mathcal{E} \sim O\left(\left(\frac{1}{N}\right)^{\frac{1}{d}}\right)$

### Computational Complexity per Sample

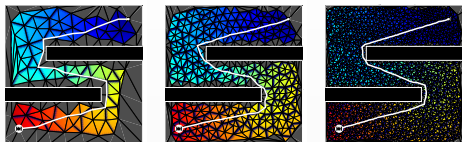
Sampling	$O(1)$
Delaunay refinement	$O(\log(N))$
Sample localization	$O(\log(N))$
Simplex rewiring	$O(1)$
Collision check	$O(1)$
Repairing FMM (amortized)	$O(\log(N))$

### Running Time Complexity

per $N$ samples	$O(N \log(N))$
per digit of accuracy	$O(\mathcal{E}^{-d(1+\delta)}) \quad \forall \delta > 0$



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<http://tinyurl.com/qjnazvr>

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## Simulation Results