# An Effort Bias for Sampling-based Motion Planning

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# Introduction Problem RRT P-PRM Our Work BEAST Experiments Conclusion

Geometric Motion Planning: piano mover's problem find sequence of states

Kinodynamic Motion Planning:

racing cars find sequence of piece-wise constant controls

# The Problem: Fast Kinodynamic Motion Planning

Introduction
Problem
■ RRT
■ P-PRM
■ Our Work
BEAST
Experiments

Conclusion





- $\bullet$  Dijkstra (1959)
- $A^*$  (1968)
- Sampling-based approach:
  - $\bullet \quad \text{RRT} \ (1999)$

# The Problem: Fast Kinodynamic Motion Planning

Introduction
Problem
■ RRT
■ P-PRM
■ Our Work
BEAST

Experiments

Conclusion





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Introduction	
Problem	
■ RRT	
■ P-PRM	
■ Our Work	
BEAST	
Experiments	ЛЛ
Conclusion	
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#### troduction

Kinodynamic Motion Planning

RRT

P-PRM

Our Work

#### inimizing planning time: BEAST

Local Effort Estimates **Global Effort Estimates** 

#### *cperiments*

Environments

Results

Introduction Problem ■ RRT ■ P-PRM Our Work BEAST Experiments Conclusion



- Given: environment, start state, goal region, vehicle dynamics
- Find: dynamically-feasible continuous trajectory (sequence of piece-wise constant controls)





Generate a (random) sample state

Introduction Problem RRT ■ P-PRM Our Work BEAST Experiments Conclusion 



Generate a (random) sample state
Select nearest state in the existing motion tree

Introduction
Problem
RRT
P-PRM
Our Work
BEAST
Experiments
Conclusion



- Generate a (random) sample state
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- Steer toward the sample, generating new state (or use several random controls if no steering)





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  - Repeatedly grow the motion tree until it touchs the goal region





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- Problem
- □ RRT
- P-PRM
- Our Work

BEAST

Experiments

Conclusion



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- Problem
- □ RRT
- P-PRM
- $\blacksquare$  Our Work

BEAST

Experiments

Conclusion



- General only forward simulator required
- Voronoi bias to encourage coverage
- More recent work (EST, KPIECE) also emphasizes coverage

#### coverage $\neq$ fast planning

# Cost-guided Planning: P-PRM (Le & Plaku 2014)







#### Abstract the state space:



Randomly sample low dimensional abstract states (Use as vertices, each Vertex represent an abstract region)



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- Connect neighbor vertices

Introduction Problem RRT P-PRM Our Work BEAST Experiments Conclusion

Abstract the state space:



- Randomly sample low dimensional abstract vertices (Each Vertex represent an abstract region)
- Connect neighbor vertices
  - Resulting abstract graph structure

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An Effort Bias for Sampling-based Motion Planning –  $15\ /\ 37$ 





- 1. Find a shortest path from the start vertex to the goal vetex
- 2. Use heuristic cost-to-go information to guide growth of the motion tree.



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#### optimizing solution $\cos t \neq$ optimizing planning effort

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■ RRT

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An Effort Bias for Sampling-based Motion Planning -17/37

#### **Our Work: Effort-based Guidance**



Experiments

Conclusion

- 1. Explicit reasoning about planning effort
- 2. Find decent solutions faster than cost-guided methods
- 3. Combines:
  - Sampling-based motion planning
  - Heuristic graph Search
  - Online estimation of effort

Transfer new ideas from Heuristic Search to Sampling-based Motion Planning

# Outline of Talk

Problem

- RRT
- P-PRM

Our Work

BEAST

Experiments

Conclusion

Introduction Kinodynamic Motion Planning RRT P-PRM Our Work Minimizing planning time: BEAST Local Effort Estimates Global Effort Estimates Experiments Environments Results

Introduction

#### BEAST

Local Effort
 Estimates
 Global Effort
 Estimates

■ BEAST

Experiments

Conclusion

# Bayesian Effort-Aided Search Trees (BEAST)

Introduction

BEAST

■ Local Effort

Estimates

■ Global Effort

Estimates

■ BEAST

Experiments

Conclusion

# $\begin{array}{l} \mbox{Minimize planning effort} \\ \approx \mbox{Minimize $\#$ of total propagation attempts} \end{array}$



#### Local Effort Estimates



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□ Local Effort

Estimates

■ Global Effort

Estimates

■ BEAST

Experiments

Conclusion

How to estimate # of propagation attempts?Beta Distribution: current belief regarding success rate across an edge

$$E[X] = \frac{success}{success + failure}$$



Edge weight in abstract graph

= expected # of propagation for one success attempt =  $E[X]^{-1}$ 

#### Local Effort Estimates



BEAST

■ Local Effort Estimates

■ Global Effort

Estimates

■ BEAST

Experiments

Conclusion

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#### **Global Effort Estimates**











#### Initialize effort estimate





Estimate effort  $\rightarrow$  Guide motion tree growth toward easy way

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#### Beast find solution faster than P-PRM and RRT

Introduction

BEAST

Experiments

■ Environments

 $\blacksquare$  Results

Conclusion

# Experiments

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#### **Environments and Set up**

BEAST

Experiments

Environments

 $\blacksquare Results$ 

Conclusion

 Open Motion Planning Library (OMPL) ompl.kavrakilab.org RRT, KPIECE Dynamic Car, Blimp, Quadrotor
 We implemented P-PRM

Hovercraft

- 5 start-goal pairs
- $\blacksquare$  50 random seeds

(a) car and hovercraft (b) open area

\*

(c) 3 ladder (d) single wall



(e) 2D forest



(i) fifthelement



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(f) blimp

(g) quadrotor

(h) 3D forest



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Introduction

BEAST

Experiments

Environments

Results

Conclusion

Does fast planning yield high-cost plans? Goal achievement time = planning time + trajectory time (As factor of BEAST)

map	vehicle	P-PRM	KPIECE	RRT
open area	car	1.0-1.1	1.8–2.3	1.0-1.2
	hover.	1.0–1.1	1.6–1.9	1.4–1.8
single wall	car	1.0-1.1	1.2–1.4	1.0-1.1
	hover.	$\infty - \infty$	1.1–1.3	$\infty$ - $\infty$
3 ladder	car	1.0-1.1	1.2–1.3	1.1-1.2
	hover.	$\infty - \infty$	1.0-1.1	$\infty$ - $\infty$
2D forest	car	0.9–1.1	$\infty$ - $\infty$	1.4–1.8
	hover.	0.8–0.9	$2.8-\infty$	$\infty$ - $\infty$
3D forest	quad.	0.9–1.0	1.0–1.2	1.1–1.4
	blimp	1.0–1.1	$\infty$ - $\infty$	1.9–2.4
fifthelement	quad.	0.8–1.0	0.9–1.0	1.3–1.6
	blimp	0.9–0.9	$\infty - \infty$	1.0 - 1.3

GAT of BEAST is similar to P-PRM and better than KPIECE and RRT

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Introduction

BEAST

Experiments

Conclusion

■ Summary

## Conclusion

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### Summary

Introduction BEAST Experiments

Conclusion

Summary

- 1. Explicit reasoning about planning effort
- 2. Find solutions faster than cost-guided planning
- 3. Continue the transfer of ideas from heuristic graph search to sampling-based motion planning:
  - Abstraction-based heuristics
  - Explicit estimates of effort
  - Online learning for metareasoning

#### **Questions?**

Introduction

BEAST

Experiments

Conclusion

Questions

Questions?



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Introduction

BEAST

Experiments

Conclusion

Back-up Slides

■ Limitation■ InternalSampling

# **Back-up Slides**

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### Limitation



BEAST

Experiments

Conclusion

Back-up Slides

Limitation
Internal
Sampling

- If abstract misses important aspects of the problem,
   BEAST may not provide much speed-up
  - If the problem is very simple, the overhead of forming and maintaining the abstraction may not be worth the possible decrease in state propagation and collision checking Ignore solution cost

### **Internal Sampling**

Introduction

BEAST

Experiments

Conclusion

Back-up Slides
Limitation
Internal
Sampling

Benefit of internal sampling? Add more samples to the destination region so that increase the chance it can further propagate outward.

$$te(e) = ee(e) + \min_{e_2 \in e.out} \frac{e_2 \cdot \alpha + e_2 \cdot \beta + 1/n}{e_2 \cdot \alpha + 1/n} + te(e_2 \cdot dest)$$



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