

# Informative Path Planning with a Human Path Constraint

Daqing Yi

Department of Computer Science  
Brigham Young University

# Outline

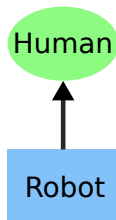
## Structure



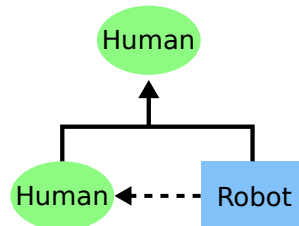
- 1 Introduction
- 2 Problem definition
  - Informative path
  - Human constraint
  - The optimization model
- 3 Solution
  - Backtracking heuristic
  - Anytime algorithm design
- 4 Simulation
  - Robot wingman
  - Results
- 5 Summary

# Human-robot collaboration

## Introduction



**Human-robot  
interaction**

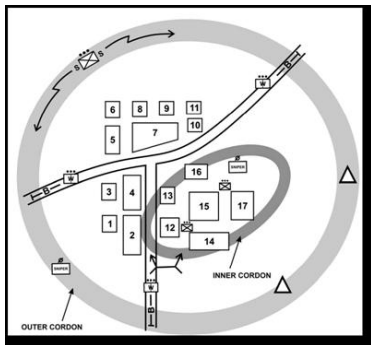


**Human-robot collaboration**



# Cordon and search

## Introduction

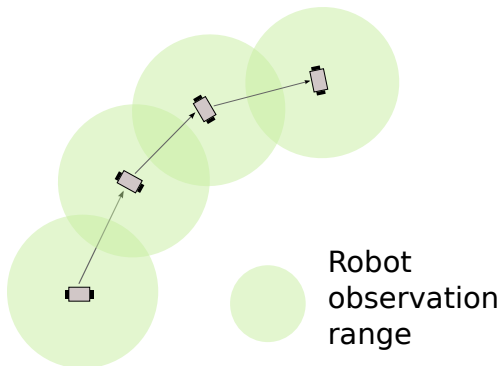


# Coverage model

## Informative path

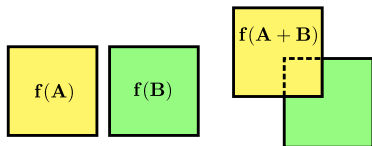


- Maximum coverage problem
- Information gain - entropy



# Submodularity

## Informative path



$$f(A) + f(B) \geq f(A + B)$$

## Information

- search space  $S$
- the observation of a robot  $\mathbf{O}^X$
- the observation of a human  $\mathbf{O}^Y$

$$f(\mathbf{S}, \mathbf{O}^X) + f(\mathbf{S}, \mathbf{O}^{Y^h}) \geq f(\mathbf{S}, \mathbf{O}^X, \mathbf{O}^{Y^h})$$

# Submodular orienteering

## Informative path



### Conditional mutual information

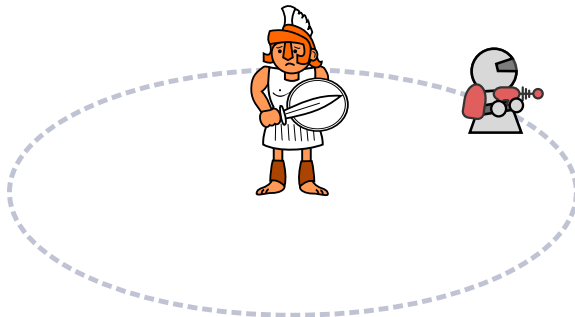
$$I(\mathbf{S}; \mathbf{O}^X \mid \mathbf{O}^{Y^h}) = H(\mathbf{S} \mid \mathbf{O}^{Y^h}) - H(\mathbf{S} \mid \mathbf{O}^X, \mathbf{O}^{Y^h})$$

- Entropy reduction
- Submodularity
- Chain rule

$$I(\mathbf{S}; \mathbf{O}^X \mid \mathbf{O}^{Y^h}) = \sum_{t=1}^T I(o_t^X; \mathbf{S} \mid o_1^X, \dots, o_{t-1}^X, \mathbf{O}^{Y^h})$$

# Team role

## Human constraint

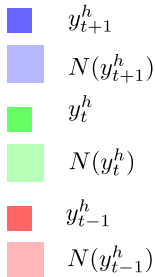
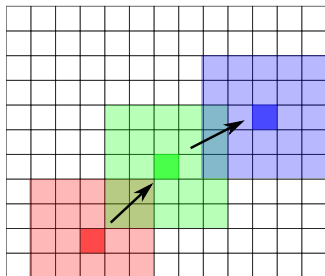


- cooperative observation
- assistance and protection



# Neighboring function

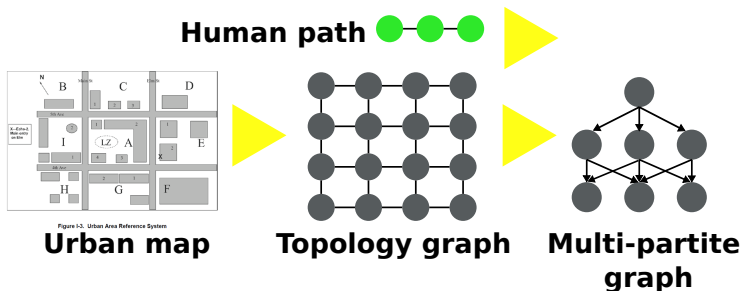
## Human constraint



- human path  $\{y_1^h \cdots y_T^h\}$
- neighboring function  $N(y_t^h)$

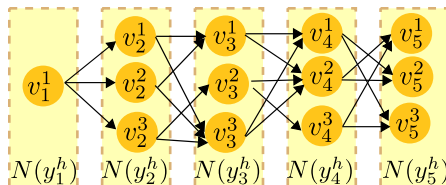
# Problem abstraction

## The optimization model



# The multi-partite graph

The optimization model



# A pruning process

The optimization model

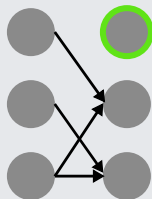


## Forward pruning

Reachable

$$\forall t \in \{2, \dots, T\},$$

$$\forall v \in V(t), \deg^-(v) > 0$$

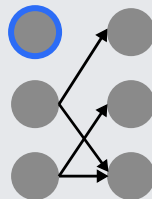


## Backward pruning

Non-terminating

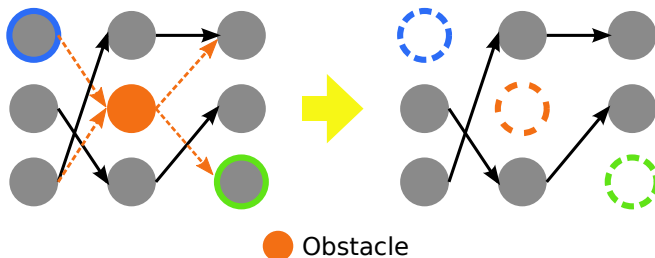
$$\forall t \in \{1, \dots, T-1\},$$

$$\forall v \in V(t), \deg^+(v) > 0$$



# Obstacles

## The optimization model



# Submodular orienteering on a multi-partite graph

## The optimization problem



$$\textit{Objective} : X^* = \arg \max_X f(X);$$

$$\textit{Constraint} : |X| = T, x_t \in V(t), (x_t, x_{t+1}) \in E.$$

# Bellman-like equation

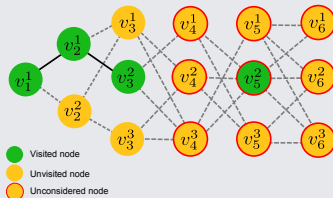
## Heuristic



$$\hat{x}_t = \arg \max_{x_t} [f(x_t \mid x_1, \dots, x_{t-1}) + \max_{x_{t+1}, \dots, x_T} f(x_{t+1}, \dots, x_T \mid x_1, \dots, x_t)]$$

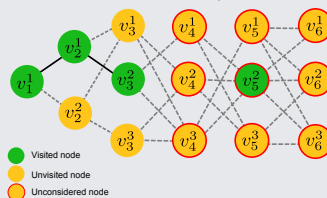
### Maximum future reward

$$\max f(x_6, \dots, x_T \mid v_1^1, v_2^1, v_3^2, v_5^2)$$

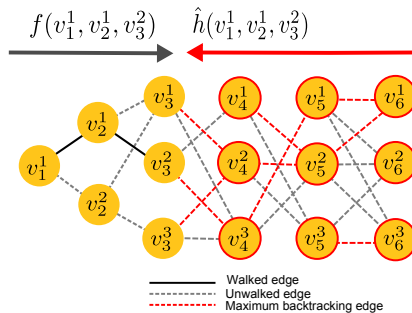


### Maximum total reward

$$f(v_5^2 \mid v_1^1, v_2^1, v_3^2) \quad h(v_1^1, v_2^1, v_3^2, v_5^2)$$



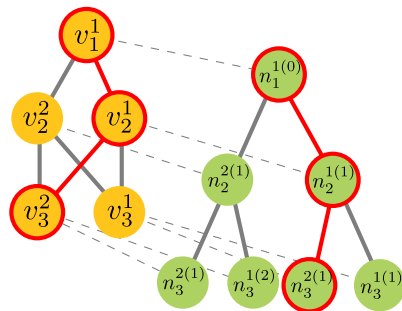
# Backtracking Heuristic





# Expanding tree

Anytime algorithm framework



- depth-first recursive traverse
- tracking the search process
- estimation storage

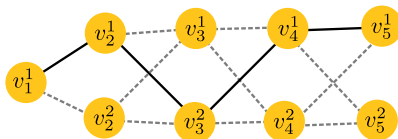
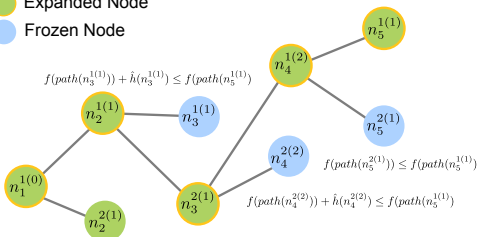
- node in an expanding tree
- vertex in a multi-partite graph

# Node freeze

Anytime algorithm framework

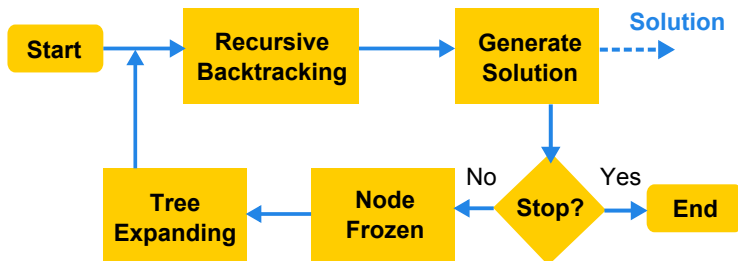


- New Node
- Expanded Node
- Frozen Node



# Flow

Anytime algorithm framework



# Performance guarantee

Anytime algorithm framework



## Lemma

*Backtracking in Algorithm 1 never **underestimates** the maximum total reward, which means*

$$\forall t \geq t', \hat{u}(x_t \mid v_1, \dots, v_{t'}) \geq u(x_t \mid v_1, \dots, v_{t'}).$$

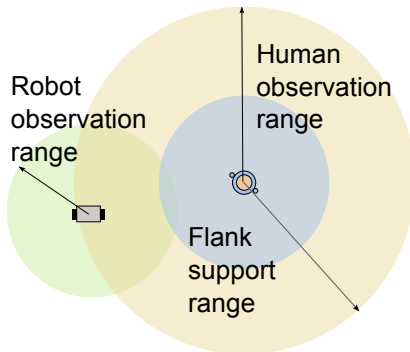


## Theorem

*The anytime algorithm framework in Algorithm 4 can always find an **optimal** solution given enough time.*

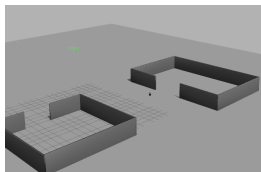
# A robot Wingman problem

## Robot Wingman



# Labelling

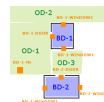
## Robot wingman



World in Gazebo simulator



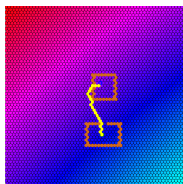
World map



Labelled world map

# Path planning

## Robot wingman



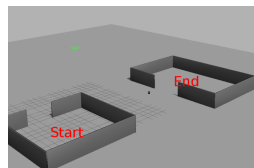
Hexagonal map



Map Start Stop



Planned path



Robot execution

# Metrics

## Results



- **Problem size**

nodeNum(fully expanding tree)

- **Percentage of nodes explored**

nodeNum(current expanding tree) / nodeNum(fully expanding tree)

- **Percentage of optimal at first run**

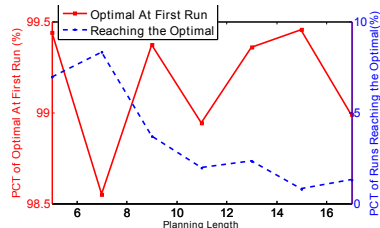
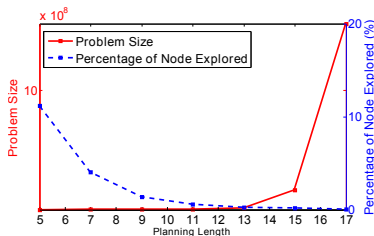
score(first found solution) / score(optimal solution)

- **Percentage of runs reaching the optimal**

iterationCount(optimal found) / iterationCount(finish tree expanding)



# Performance Results

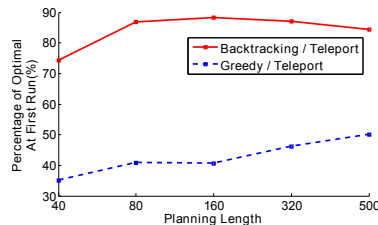
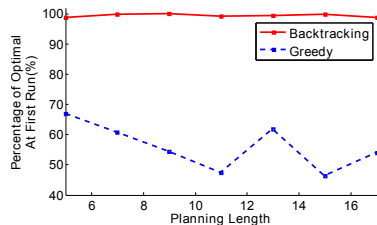


# Compare with greedy heuristic

## Performance



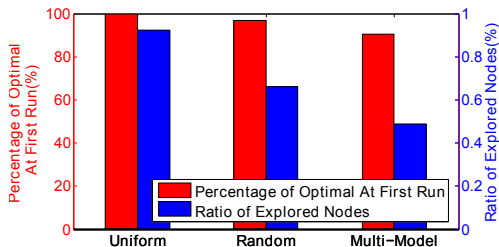
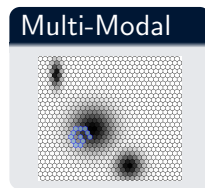
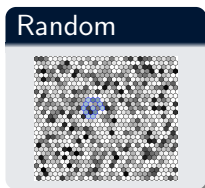
The performance of the heuristic (Percentage of optimal at first run)





# Environment difference

## Robustness

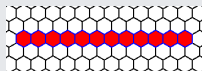


# Human path difference

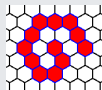
## Robustness



### Line



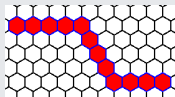
### Spiral



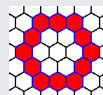
### Lawn mower



### Arc

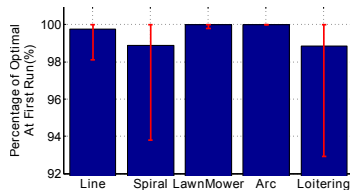
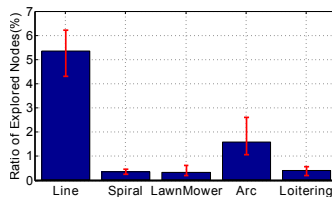
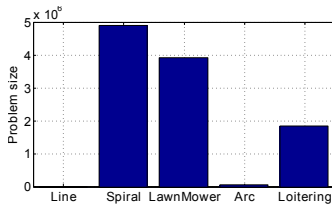


### Loitering



# Human path difference

## Robustness





# Summary

- Search space reduction by **human constraint**
- Effectiveness and efficiency of **backtracking** on a multi-partite graph
- Vertex duplication in multi-partite graph → Over-estimation increase
- Offline planning → Online planning
- Single objective → Multiple objectives

Thank you!