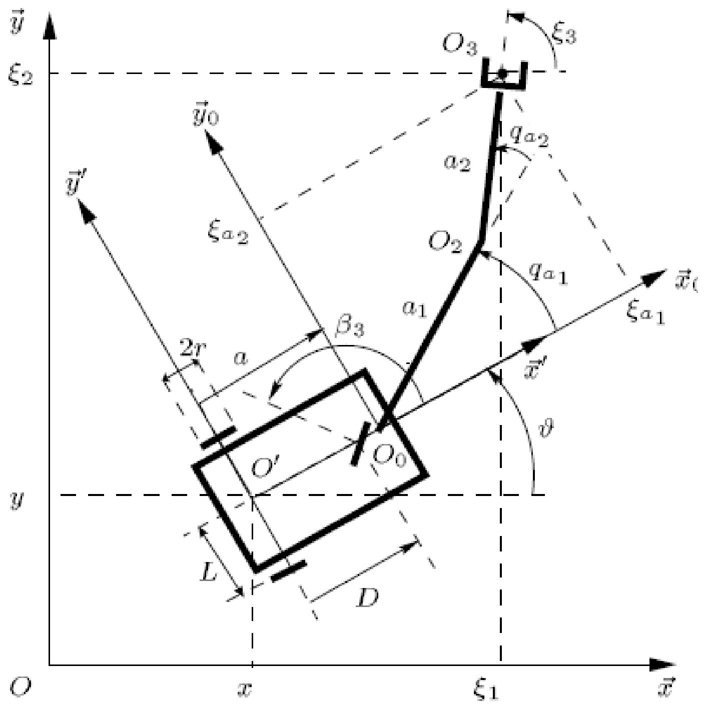
Loco-manipulation

Jane Li

Assistant Professor
Mechanical Engineering Department, Robotic Engineering Program
Worcester Polytechnic Institute

Quiz (10 pts)

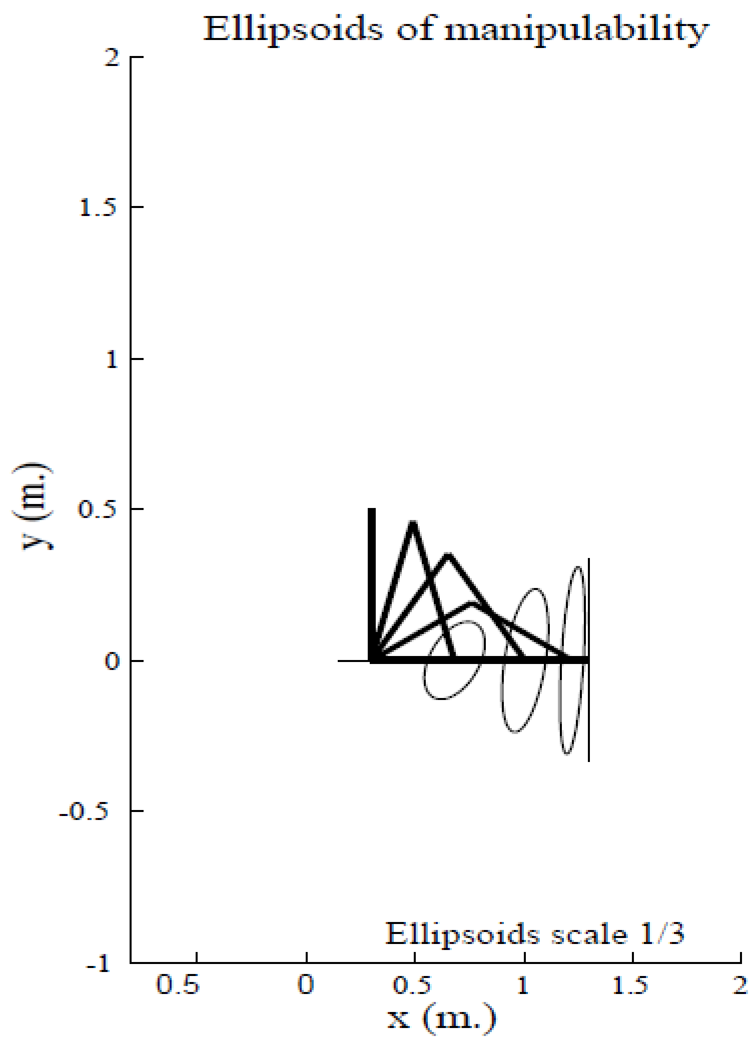
- (6 pts)A 2-DOF manipulator arm is attached to a mobile base with non-holonomic constraints. How does the mobile base affect the manipulability when the 2-DOF is at its singularity configuration?

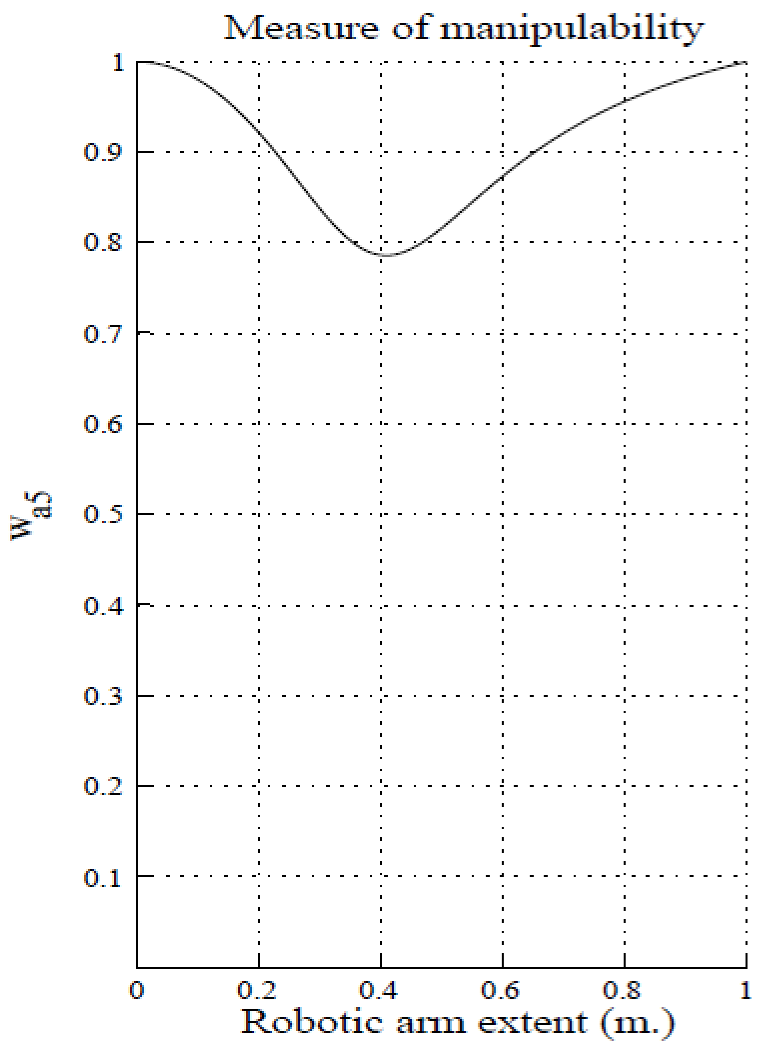


- (2 pts) What is loco-manipulation affordance?

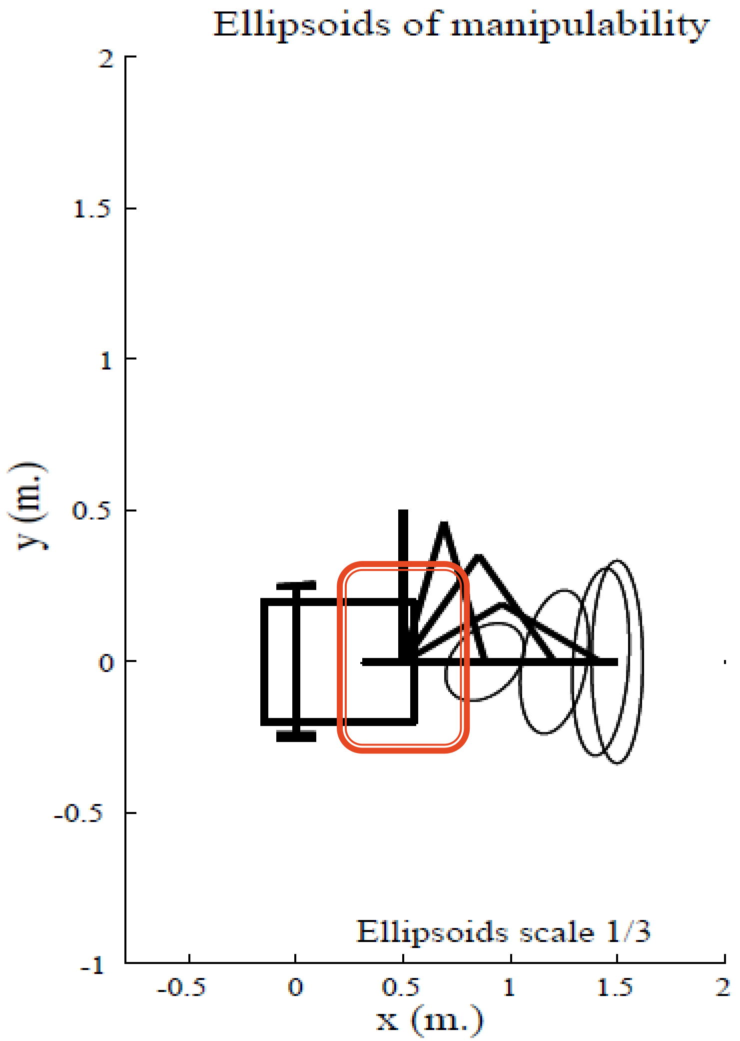
- (2 pts) How to extract loco-manipulation affordance given a RGB+D camera?

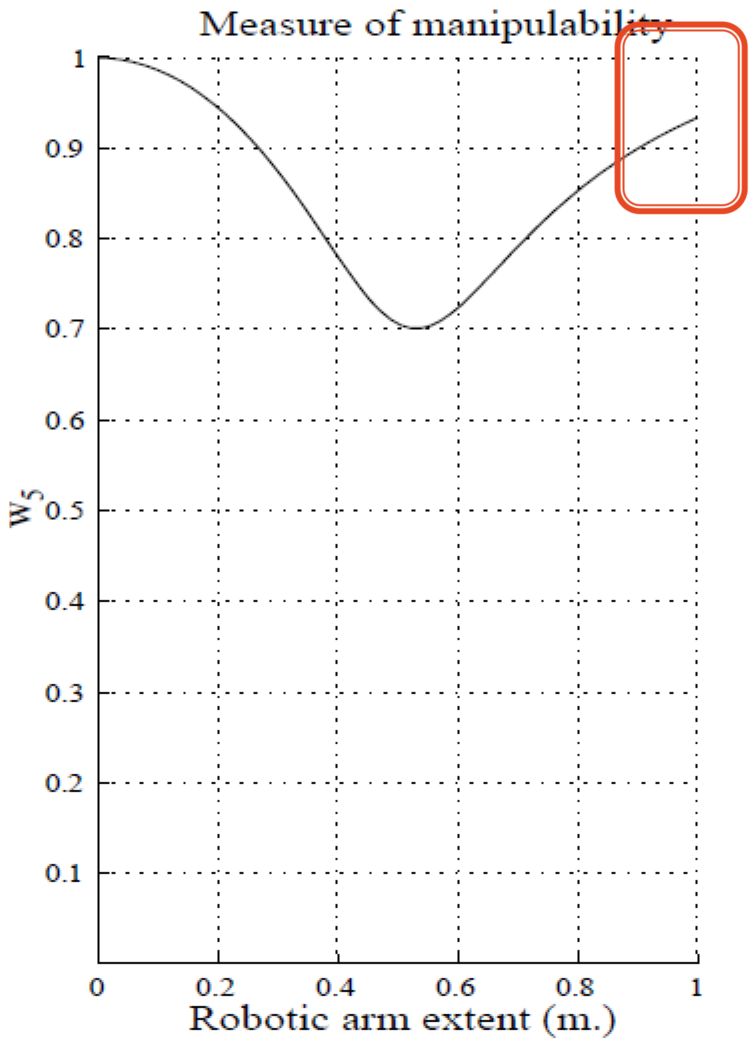
Manipulability of 2-DOF arm



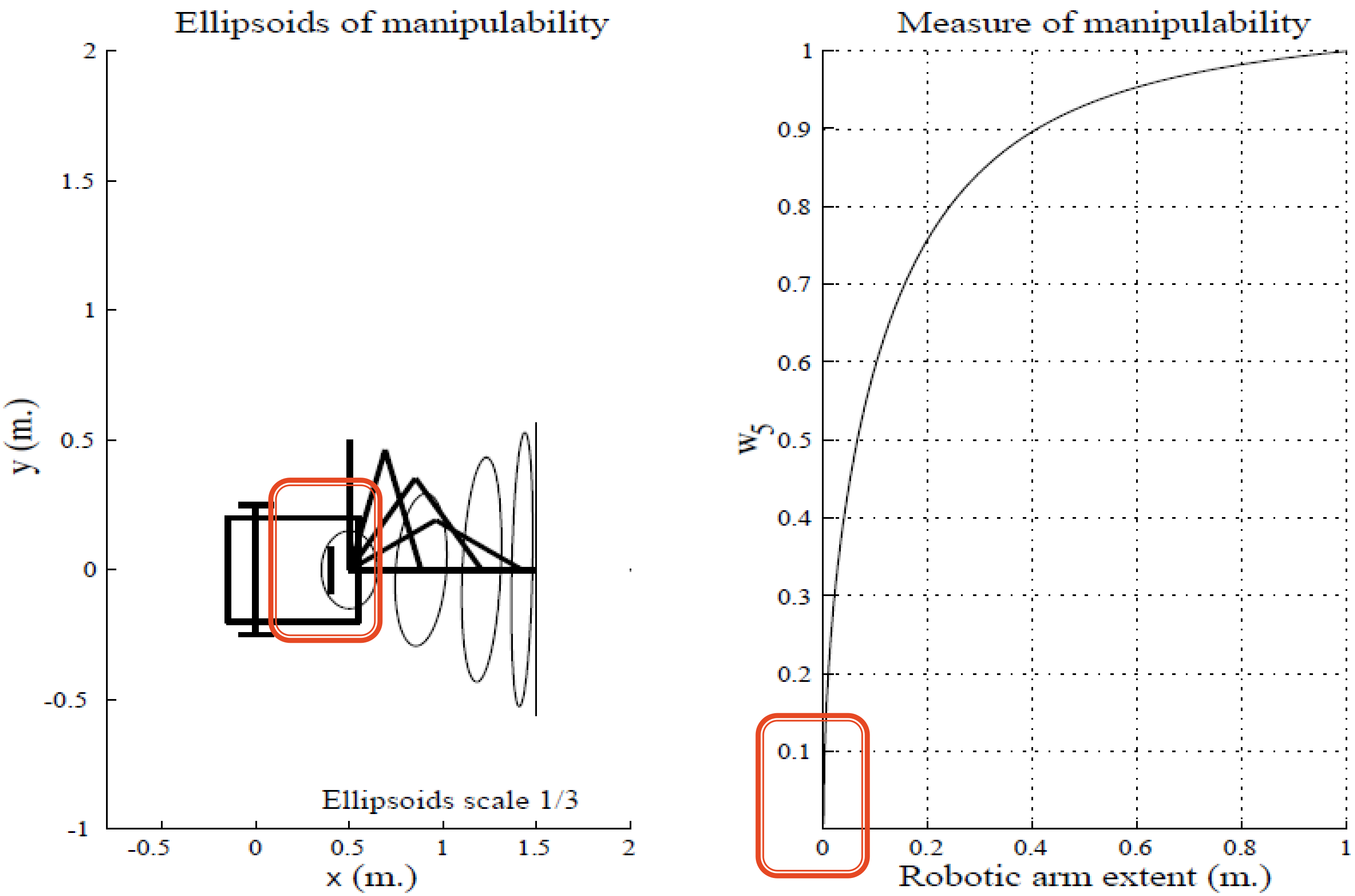


Manipulability of mobile manipulator





Manipulability of mobile manipulator

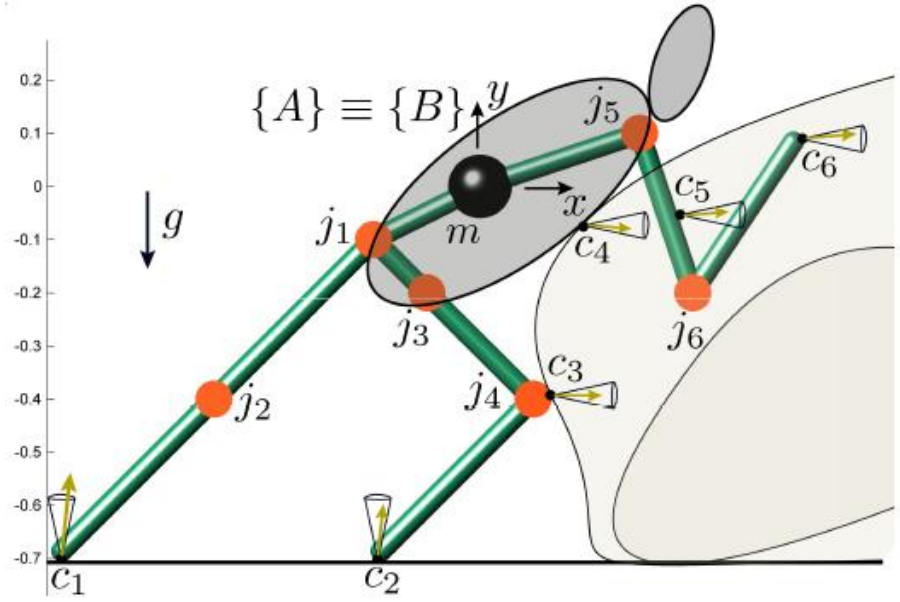


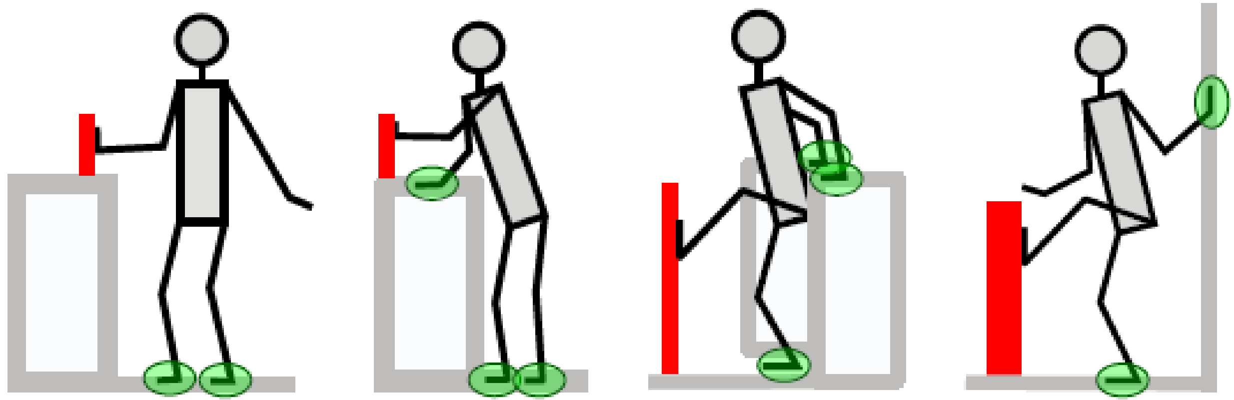
Affordance of loco-manipulation

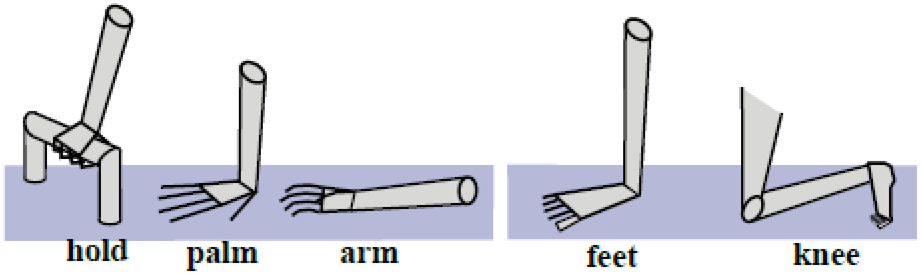
- Loco-manipulation affordance
  - Actions that involve the whole body for stabilization, locomotion or manipulation

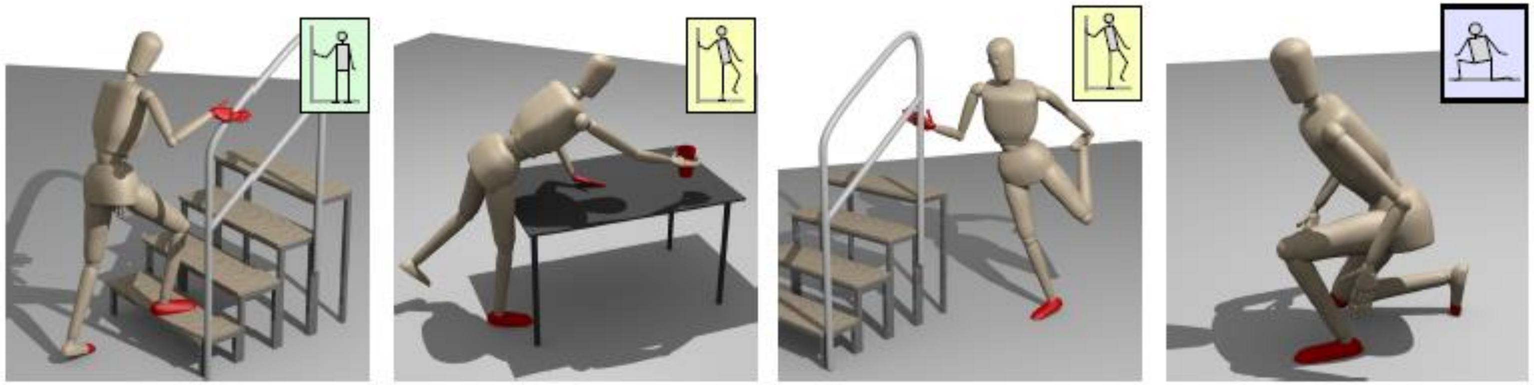
- Affordance validation
  - Assign whole-body affordance to environmental primitives, based on their shape, orientation and extent
  - Use perception feedback to validate the affordance hypotheses
  - Execute the task

Typical loco-manipulation tasks









Affordance extraction

Registered point cloud

↓

Segmentation

↓

Geometric primitives

↓

Affordance hypothesis

Optional assignment

Optional assignment

- Student talk on "trajectory optimization"
  - If you need to make up for your low-score/late submission assignment
  - So far, 7 students signed up in total
  - Three lectures + additional section on the day of course review

- Reference:
  - http://www.matthewpeterkelly.com/tutorials/trajectoryOptimization

Optional assignment

- Wednesday, April 4
  - Samruddhi Kadam spkadam@wpi.edu
- Friday, April 6
  - Nalin Raut nraut@wpi.edu
  - Abhilasha Rathod arathod@wpi.edu
  - Nathaniel Goldfarb
- Wednesday, April 11
  - Max Merlin – lecture with Gunnar on high-level motion planning
  - Guled Elmi ggelmi@wpi.edu
  - Gaurav Vikhe gsvikhe@wpi.edu

Literature review student talk

- 4/13/2018
  - Bimanual team, Swarm team
- 4/18/2018
  - High-level planning

Project presentation

- 4/25/2018
  - Mobile team, Bimannual team, High-level planning
  - Surgical robot (Sam)
- 4/27/2018
  - pHRI team

Loco-Manipulation

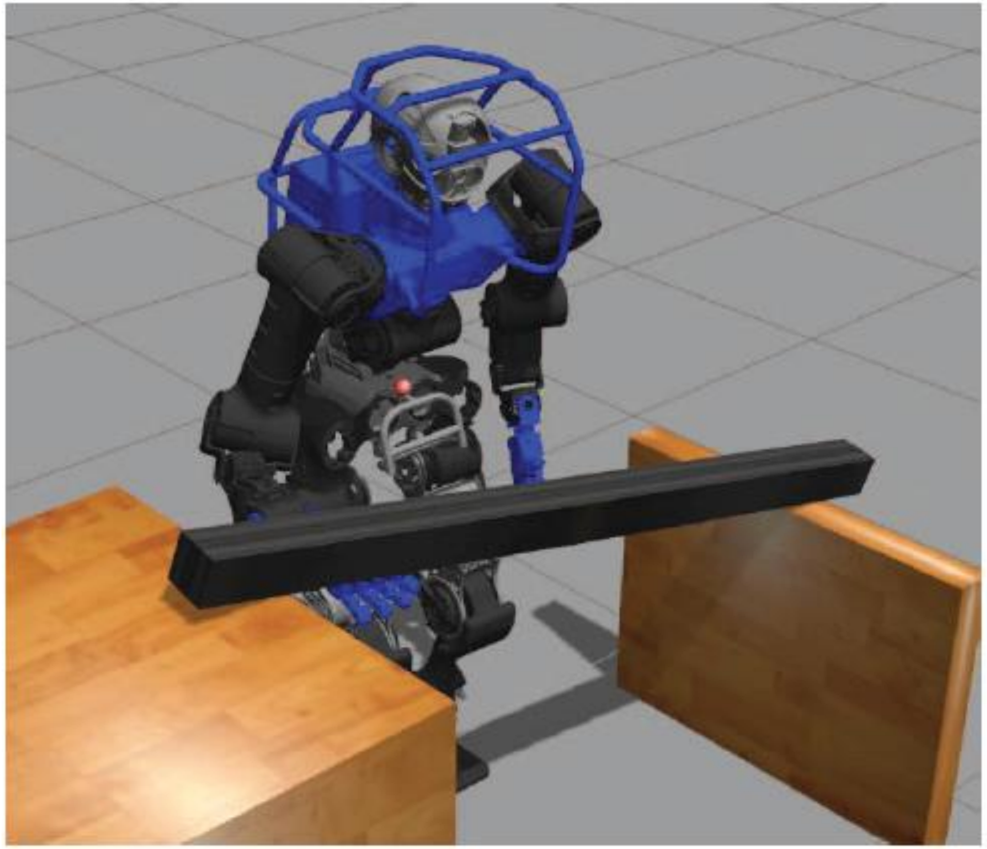
Overview

- Loco-manipulation
  - Affordance
- Loco-manipulation motion planning
  - Motion Primitives
- Motion skill transferring from humans to humanoid robots
  - Inverse optimal control

Planning loco-manipulation using motion primitives [3]

- Complex loco-manipulation can be composed using **parametrized control laws** (i.e., motion primitives)

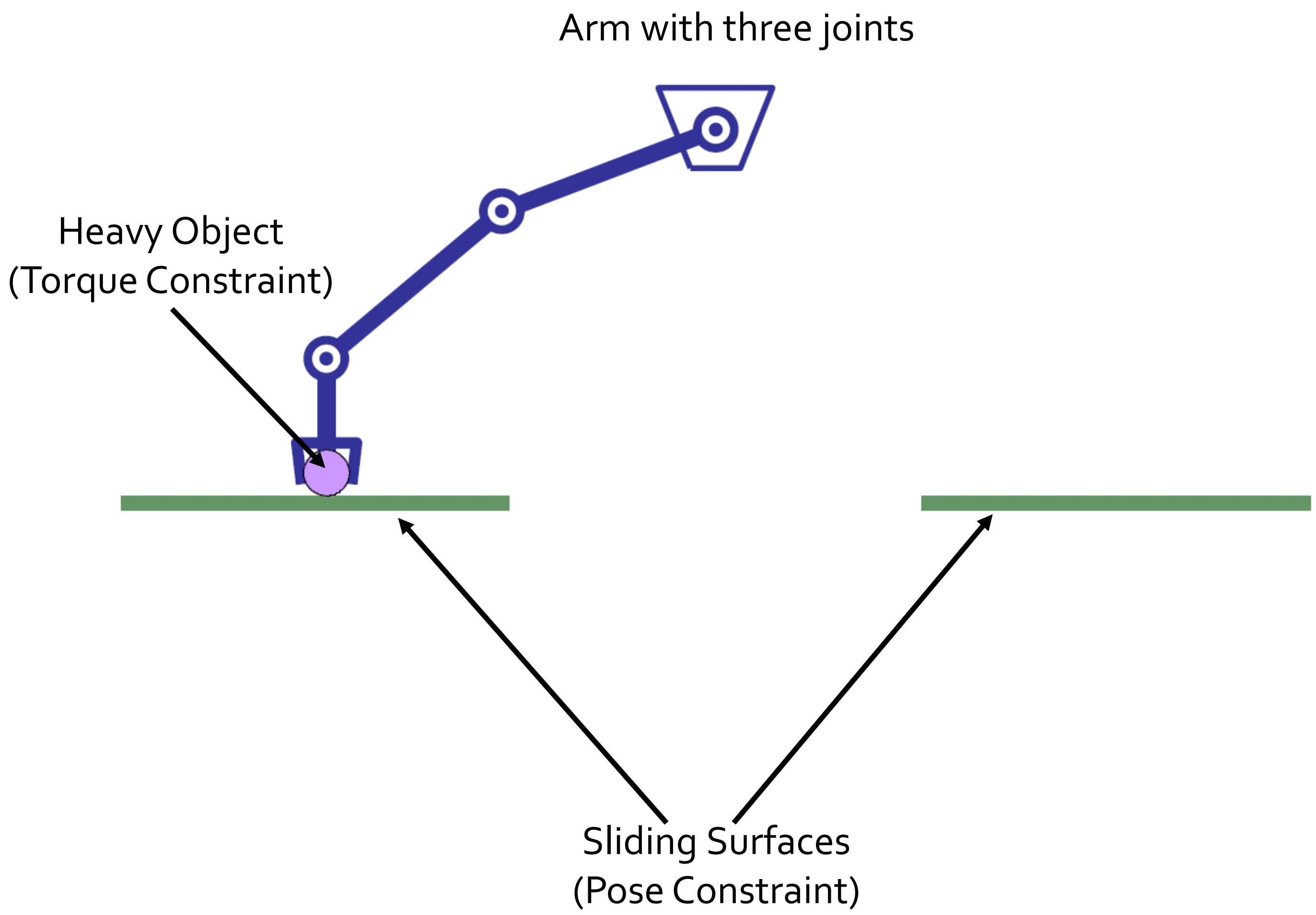
- Simultaneous execution of motion primitives may cause **instability**

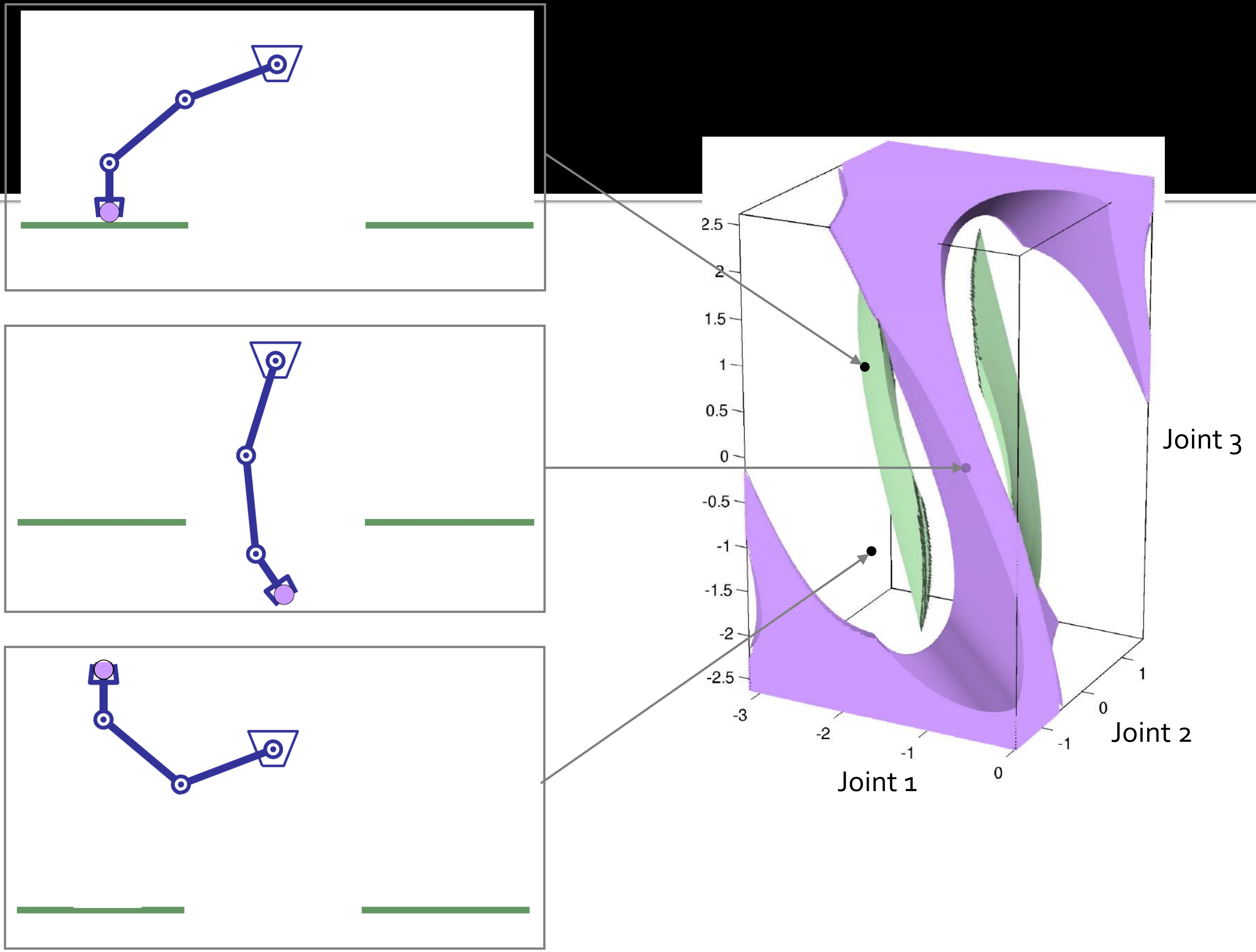


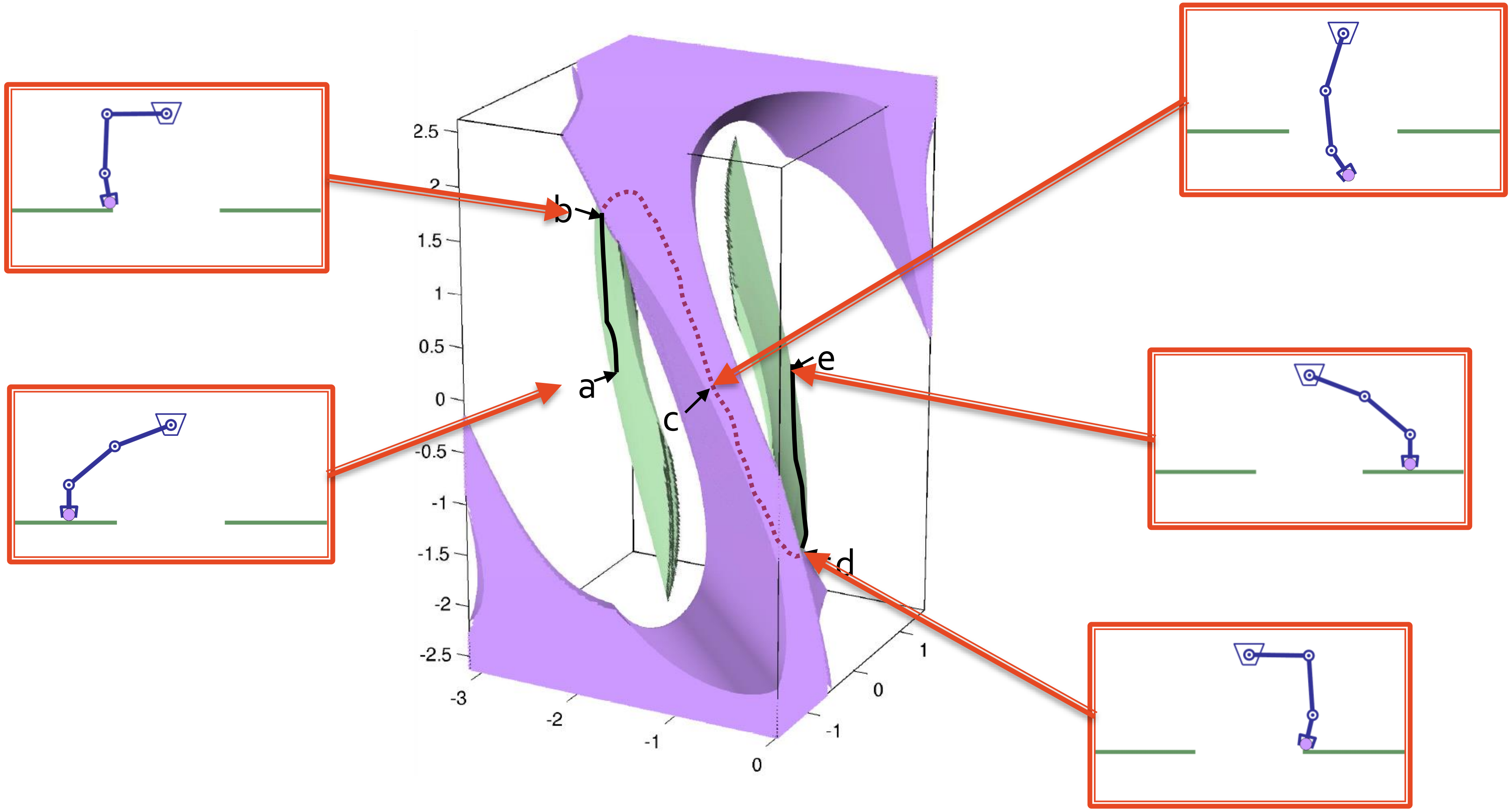
Whole-body motion planning

- Whole–body planning
  - High dimensional, numerically intractable problems
  - Multi-contacts, many constraints
- Pseudo-inverse
  - Prioritized tasks and constraints
  - Project secondary tasks to the null space of pseudo-inverse Jacobian
- Sampling-based strategy
  - Sample and search the solution in C-space
  - How to address tasks constraints?

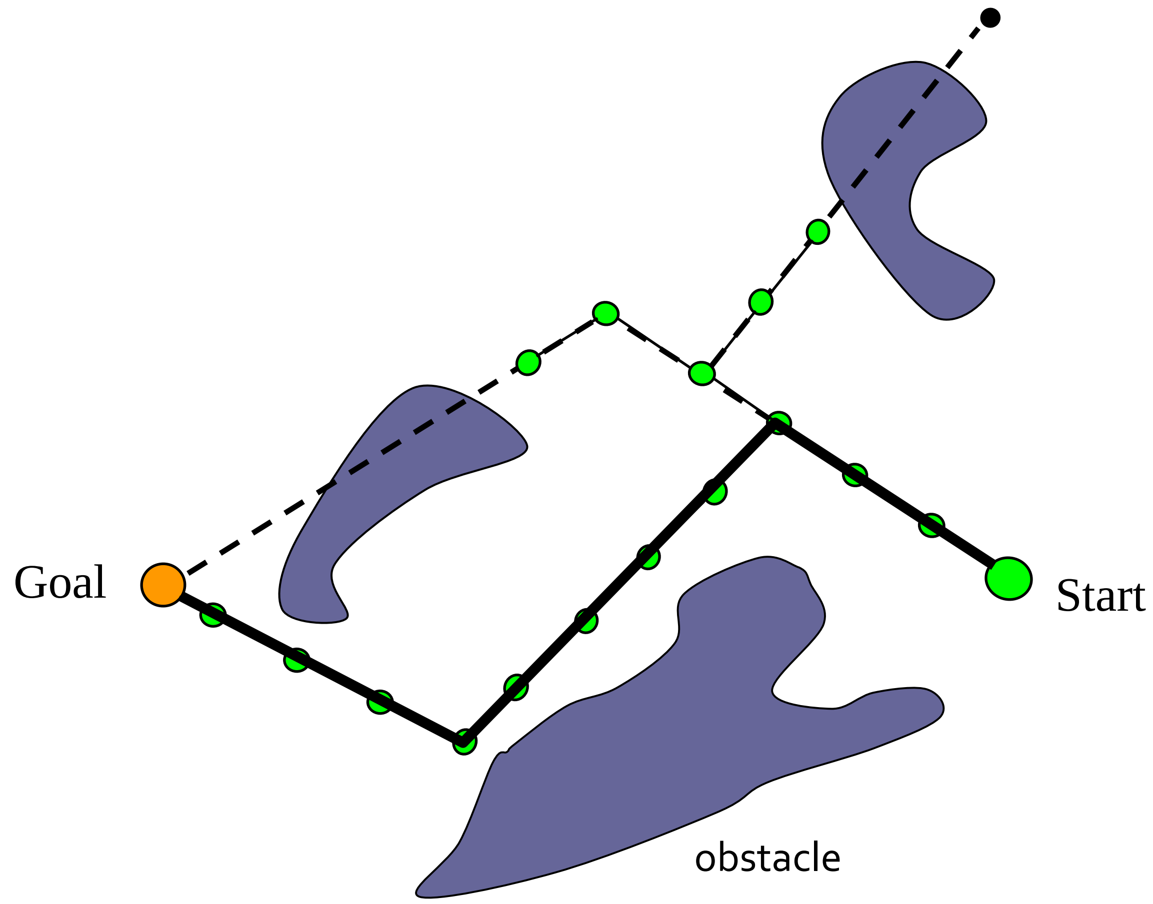
Sampling-based planning with Constraints



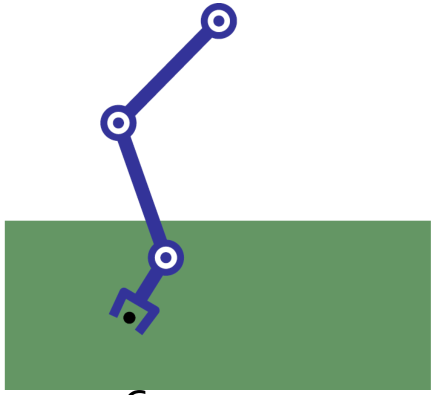

Joint 3
Joint 2
Joint 1
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-2
-1
0
1
0
-1


2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-2
-1
0
1
0
-1
a
b
c
d
e

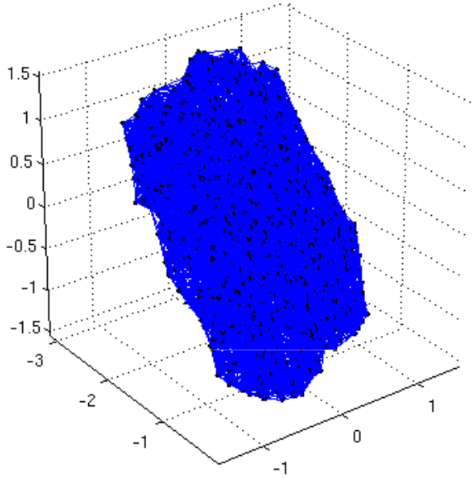
Rapidly-exploring Random Tree (RRT)



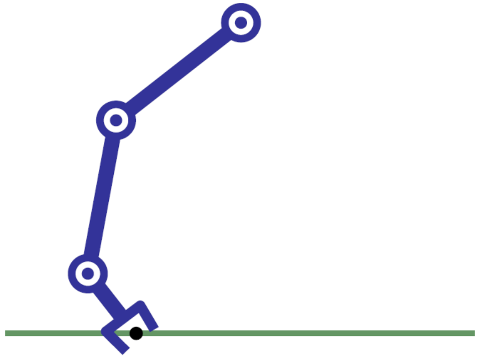
Rejection Sampling and Pose Constraints



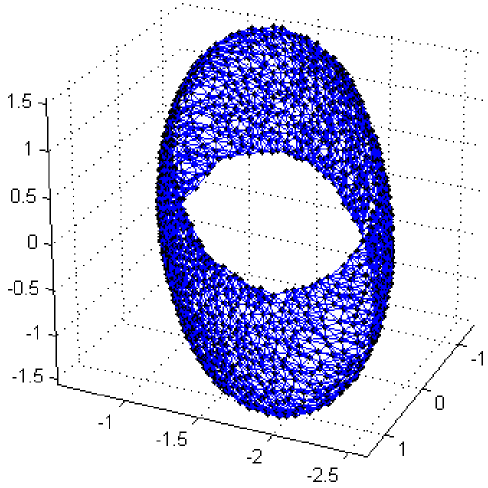
C-space



Full Dimensional



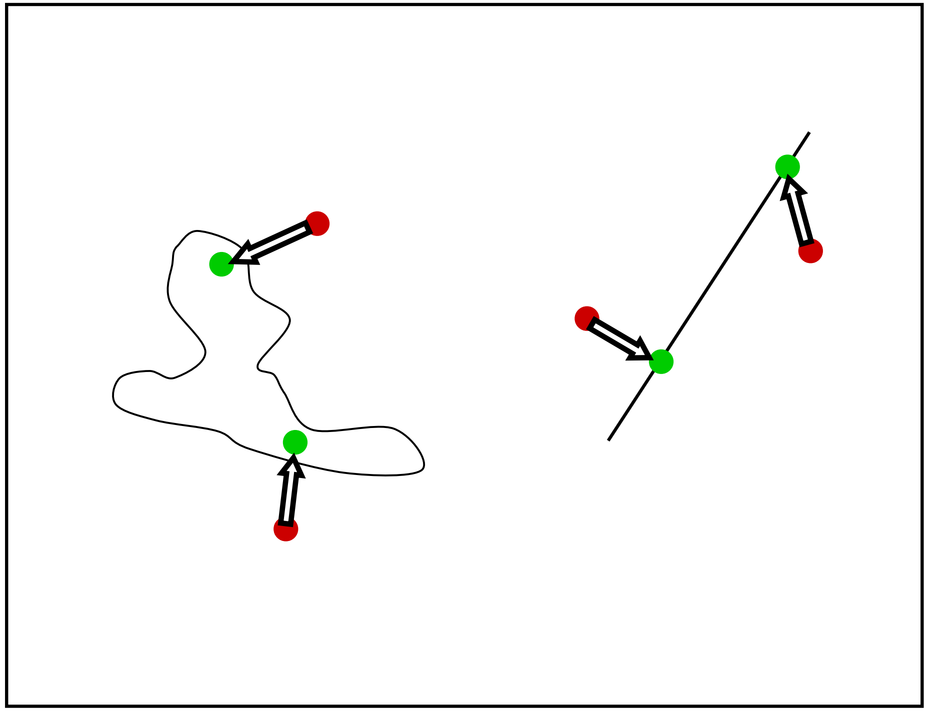
C-space



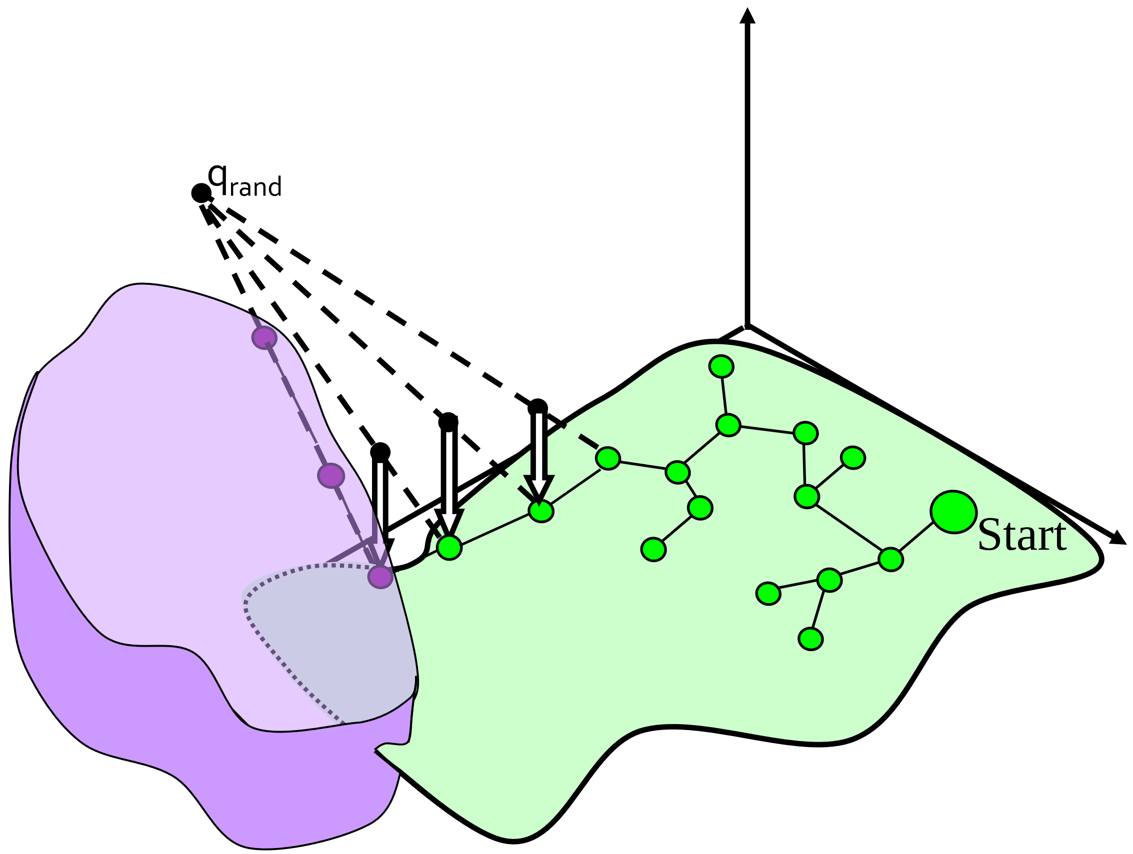
Lower Dimensional

Projection Sampling

- Sample on any manifold or dimension

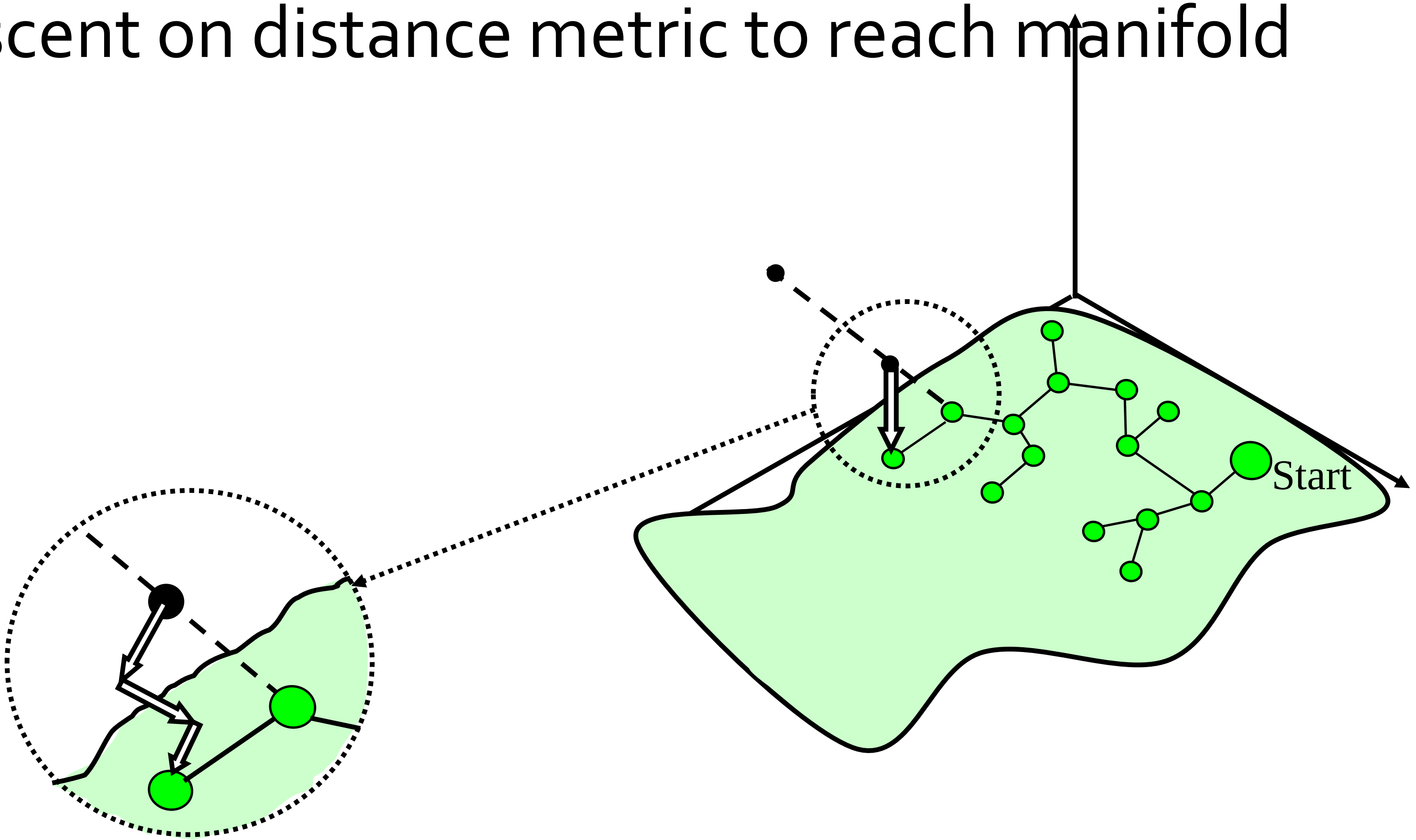


Constrained BiDirectional RRT (CBiRRT)

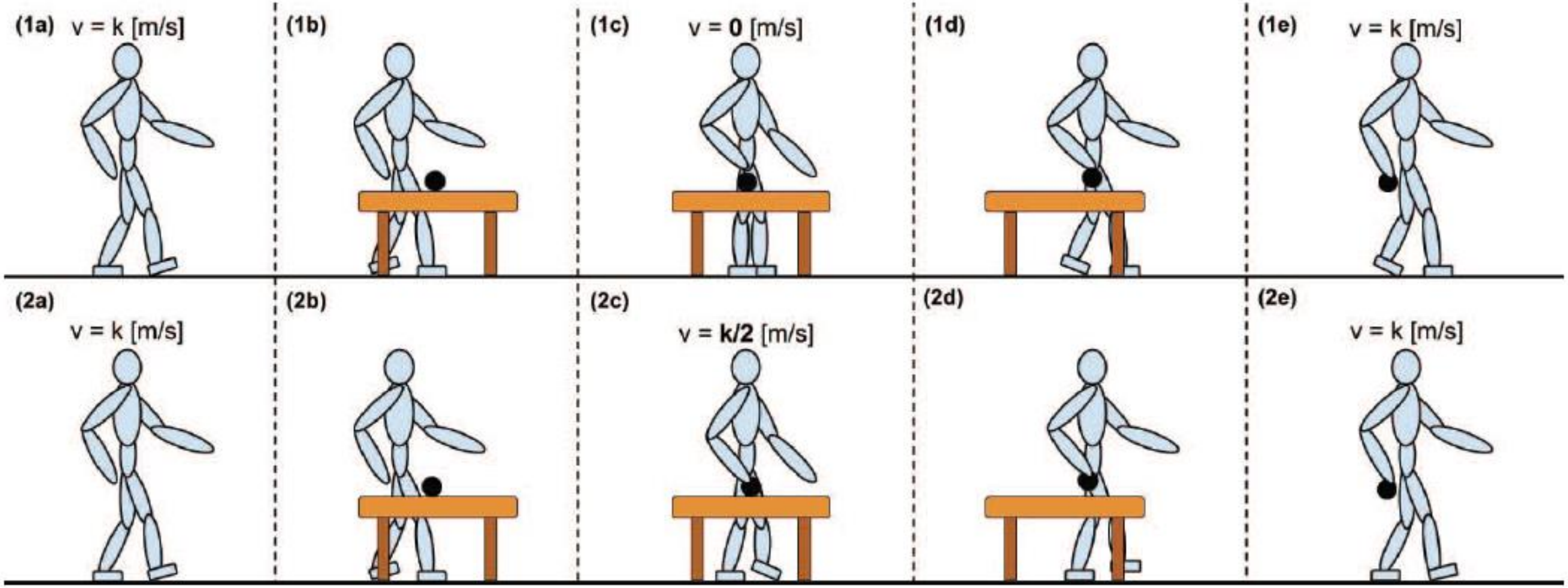


Projection Sampling

- Gradient descent on distance metric to reach manifold



Primitive-based Whole-body motion planning



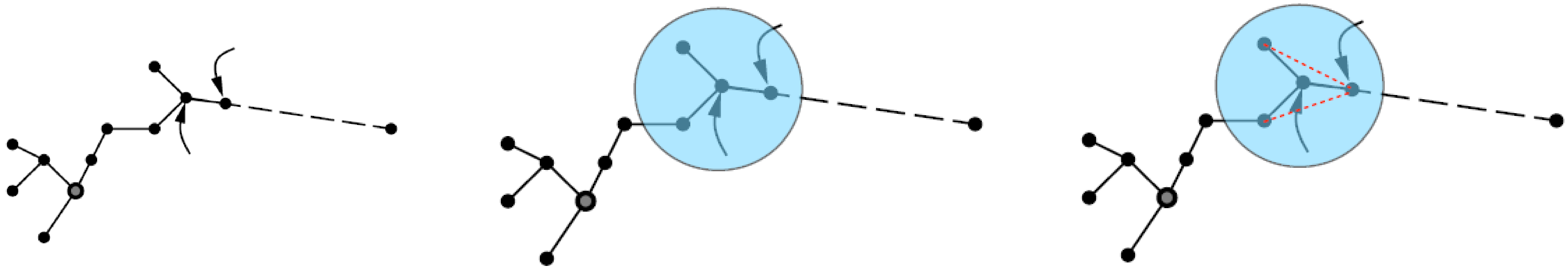
More fluent and efficient motions

P-search*

- Derived from **RRT***
- Similar to **informed RRT**
  - Use the information available from the primitives design to structure a sampling space with desirable properties

RRG

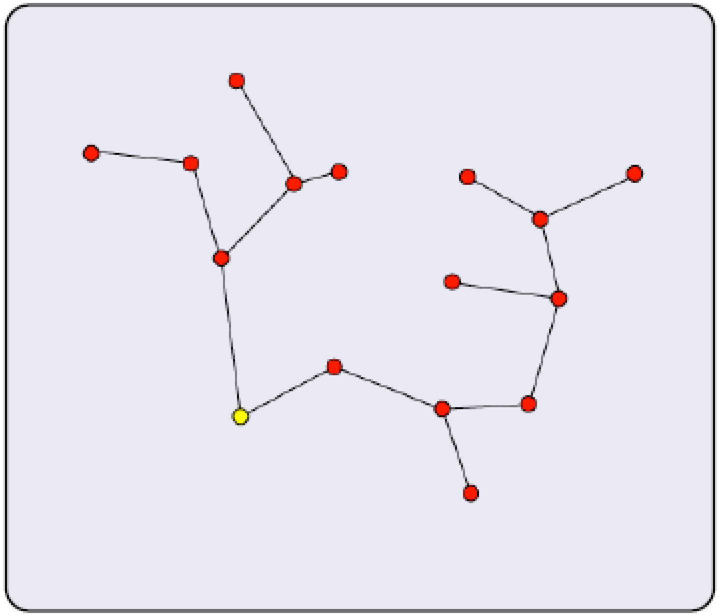
- RRT
  - Extends the nearest vertex towards the sample
- RRG
  - Extends all vertices returned by the Near procedure (if first was success).



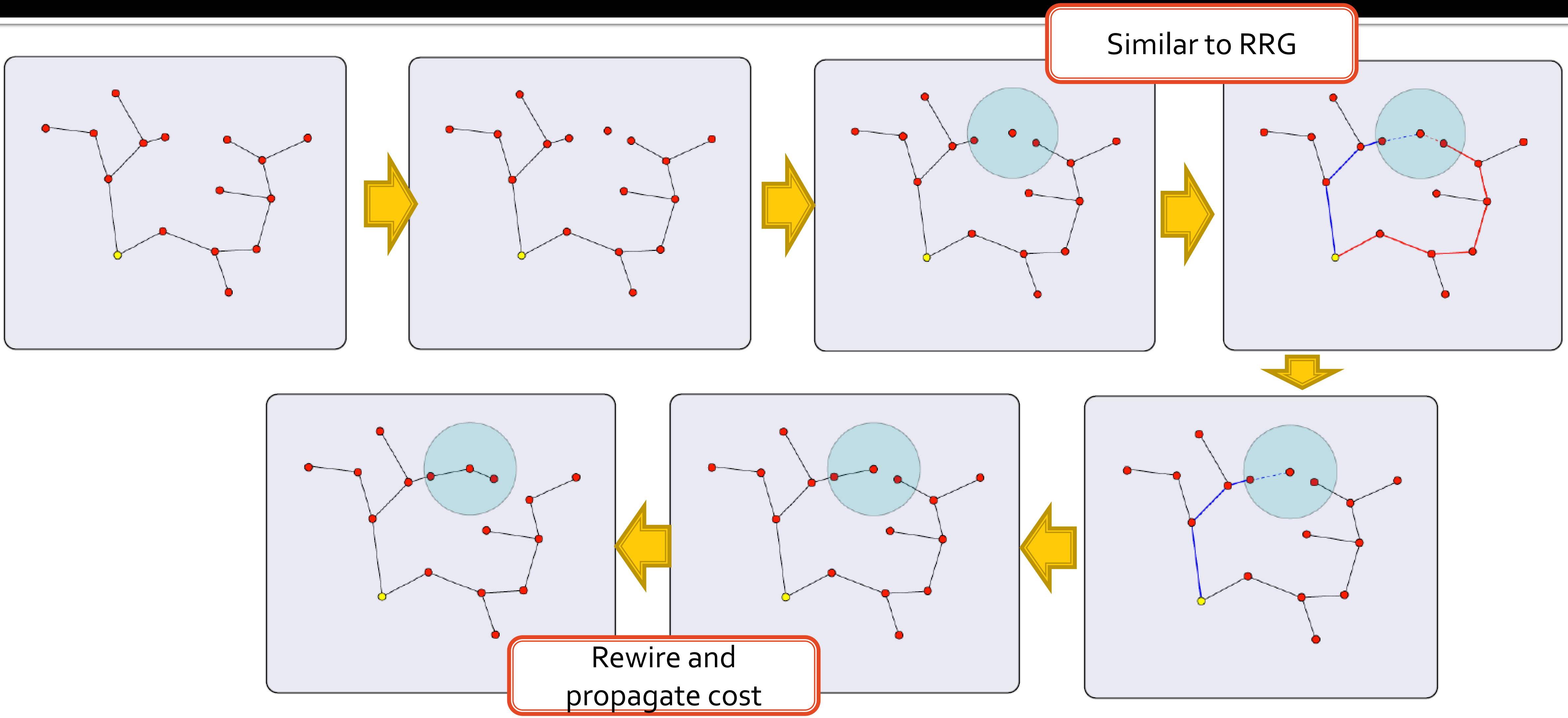
RRT*

- Similar to RRG, except for "**rewiring**" the tree as better paths are discovered.

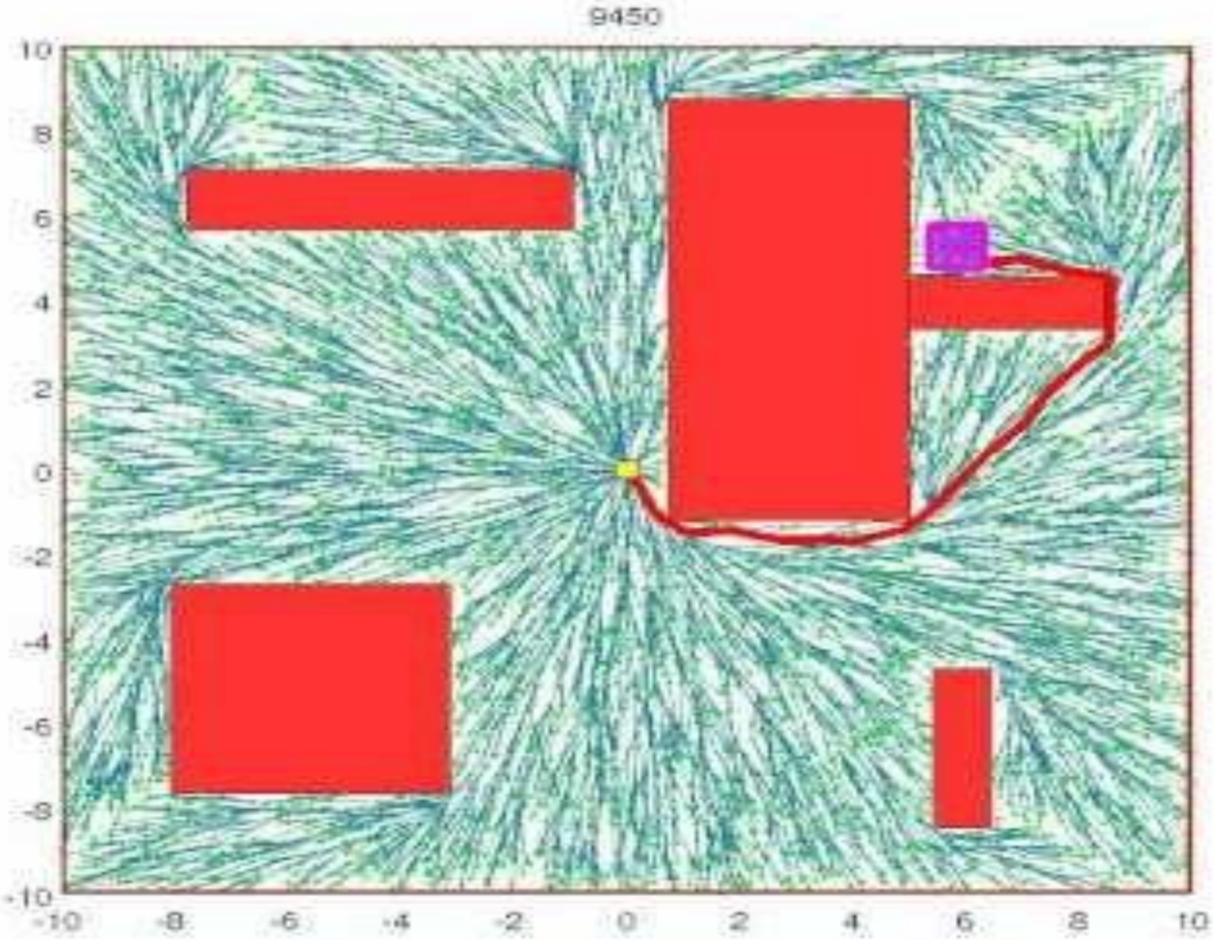
- After rewiring the **cost has to be propagated** along the leaves



RRT*



RRT*

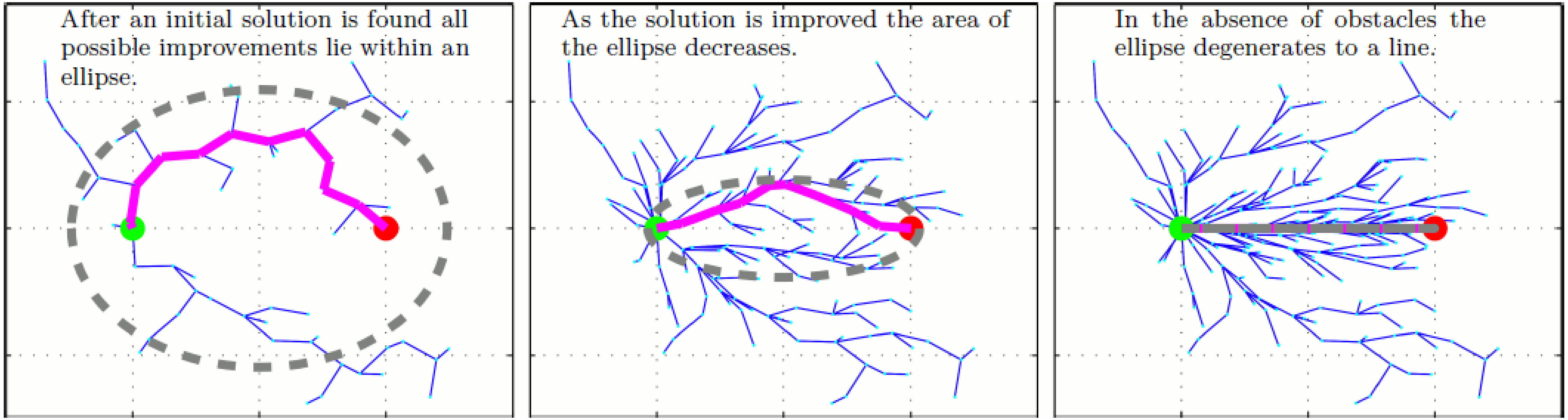


Limitation of RRT*

- RRT* is asymptotically optimal everywhere
- Not necessary for single-query planning
- Improvement
  - Limit the search to the **sub-problem** that would have a better solution
  - How to define the space of sub-problem?

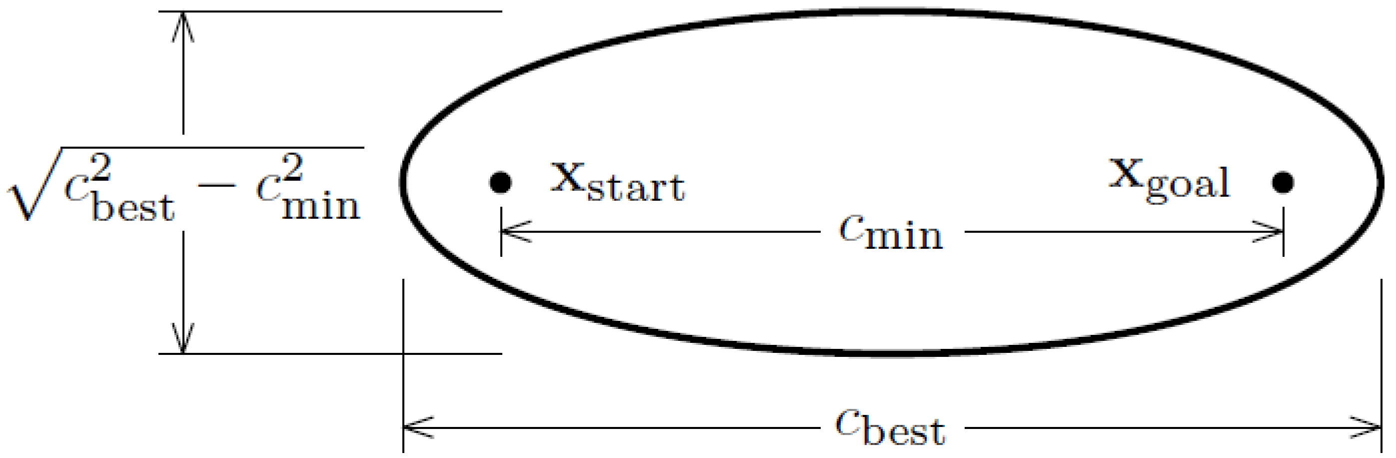
Informed RRT

- The sub-problem can be defined as "search in a n-dimensional ellipse"→ where to draw the new sample



59 iterations, $c_{\text{best}} = 148.24$ | 175 iterations, $c_{\text{best}} = 107.12$ | 1142 iterations, $c_{\text{best}} = 100$

heuristic sampling domain



$$X_{\hat{f}} = \left\{ \mathbf{x} \in X \;\middle|\; ||\mathbf{x}_{start} - \mathbf{x}||_2 + ||\mathbf{x} - \mathbf{x}_{goal}||_2 \leq c_{best} \right\}$$

Informed RRT*

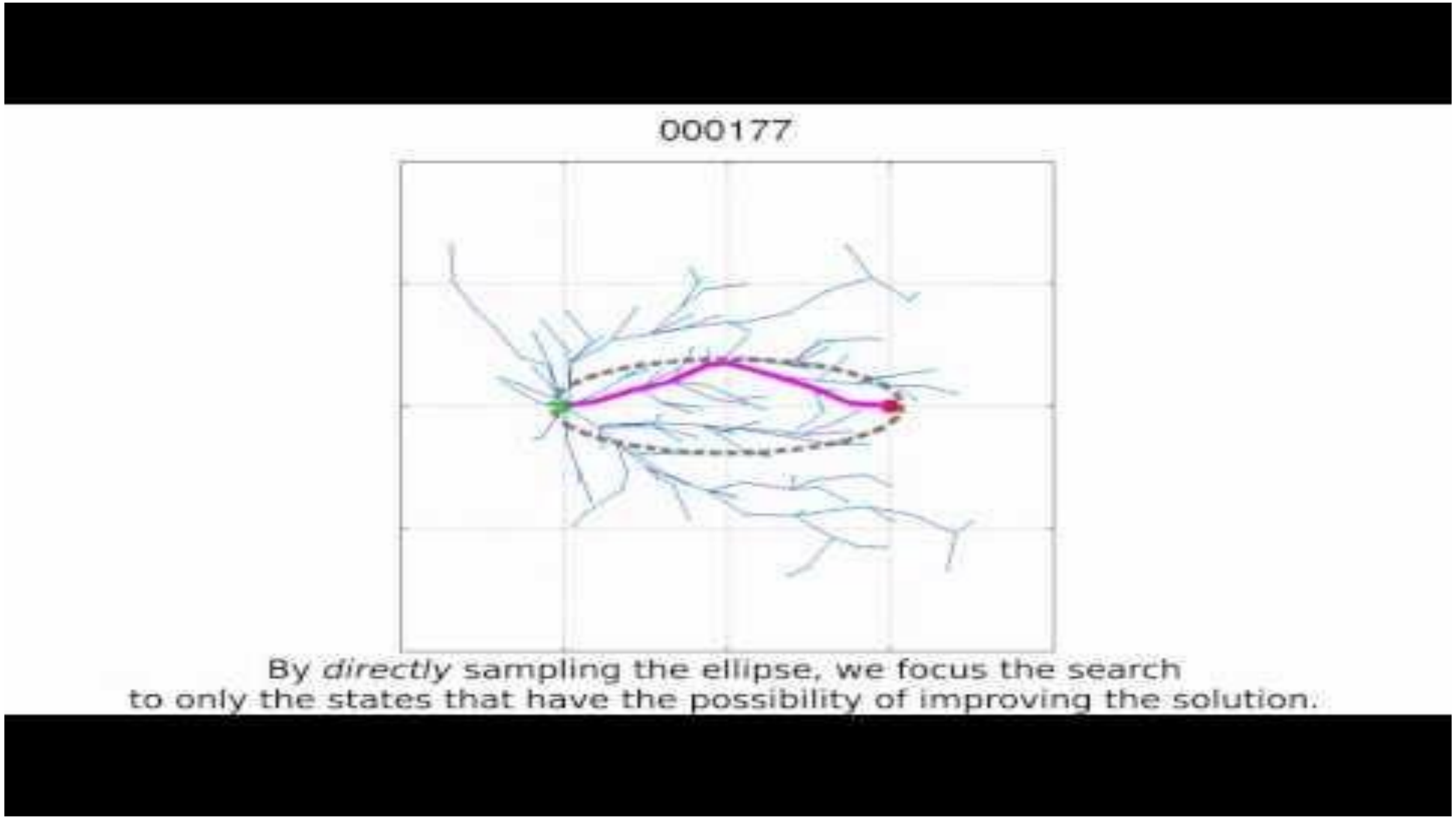
Algorithm 2: Sample $(\mathbf{x}_{start}, \mathbf{x}_{goal}, c_{max})$

if $c_{max} < \infty$ **then**
  $c_{min} \leftarrow ||\mathbf{x}_{goal} - \mathbf{x}_{start}||_2$;
  $\mathbf{x}_{centre} \leftarrow (\mathbf{x}_{start} + \mathbf{x}_{goal})/2$;
  $\mathbf{C} \leftarrow$ RotationToWorldFrame $(\mathbf{x}_{start}, \mathbf{x}_{goal})$;
  $r_1 \leftarrow c_{max}/2$;
  $\{r_i\}_{i=2,\ldots,n} \leftarrow \left(\sqrt{c_{max}^2 - c_{min}^2}\right)/2$;
  $\mathbf{L} \leftarrow \mathrm{diag}\{r_1, r_2, \ldots, r_n\}$;
  $\mathbf{x}_{ball} \leftarrow$ SampleUnitNBall;
  $\mathbf{x}_{rand} \leftarrow (\mathbf{C}\mathbf{L}\mathbf{x}_{ball} + \mathbf{x}_{centre}) \cap X$;
else
  $\mathbf{x}_{rand} \sim \mathcal{U}(X)$;
return $\mathbf{x}_{rand}$;

Algorithm 1: Informed RRT* $(\mathbf{x}_{start}, \mathbf{x}_{goal})$

$V \leftarrow \{\mathbf{x}_{start}\}$;
$E \leftarrow \emptyset$;
$X_{soln} \leftarrow \emptyset$;
$\mathcal{T} = (V, E)$;
for iteration $= 1 \ldots N$ **do**
  $c_{best} \leftarrow \min_{\mathbf{x}_{soln} \in X_{soln}} \{\text{Cost}(\mathbf{x}_{soln})\}$;
  $\mathbf{x}_{rand} \leftarrow$ Sample $(\mathbf{x}_{start}, \mathbf{x}_{goal}, c_{best})$;
  $\mathbf{x}_{nearest} \leftarrow$ Nearest $(\mathcal{T}, \mathbf{x}_{rand})$;
  $\mathbf{x}_{new} \leftarrow$ Steer $(\mathbf{x}_{nearest}, \mathbf{x}_{rand})$;
  if CollisionFree $(\mathbf{x}_{nearest}, \mathbf{x}_{new})$ **then**
    $V \leftarrow \cup \{\mathbf{x}_{new}\}$;
    $X_{near} \leftarrow$ Near $(\mathcal{T}, \mathbf{x}_{new}, r_{RRT^*})$;
    $\mathbf{x}_{min} \leftarrow \mathbf{x}_{nearest}$;
    $c_{min} \leftarrow$ Cost $(\mathbf{x}_{min}) + c \cdot$ Line $(\mathbf{x}_{nearest}, \mathbf{x}_{new})$;
    for $\forall \mathbf{x}_{near} \in X_{near}$ **do**
      $c_{new} \leftarrow$ Cost $(\mathbf{x}_{near}) + c \cdot$ Line $(\mathbf{x}_{near}, \mathbf{x}_{new})$;
      if $c_{new} < c_{min}$ **then**
        if CollisionFree $(\mathbf{x}_{near}, \mathbf{x}_{new})$ **then**
          $\mathbf{x}_{min} \leftarrow \mathbf{x}_{near}$;
          $c_{min} \leftarrow c_{new}$;
    $E \leftarrow E \cup \{(\mathbf{x}_{min}, \mathbf{x}_{new})\}$;
    for $\forall \mathbf{x}_{near} \in X_{near}$ **do**
      $c_{near} \leftarrow$ Cost $(\mathbf{x}_{near})$;
      $c_{new} \leftarrow$ Cost $(\mathbf{x}_{new}) + c \cdot$ Line $(\mathbf{x}_{new}, \mathbf{x}_{near})$;
      if $c_{new} < c_{near}$ **then**
        if CollisionFree $(\mathbf{x}_{new}, \mathbf{x}_{near})$ **then**
          $\mathbf{x}_{parent} \leftarrow$ Parent $(\mathbf{x}_{near})$;
          $E \leftarrow E \setminus \{(\mathbf{x}_{parent}, \mathbf{x}_{near})\}$;
          $E \leftarrow E \cup \{(\mathbf{x}_{new}, \mathbf{x}_{near})\}$;
    if InGoalRegion $(\mathbf{x}_{new})$ **then**
      $X_{soln} \leftarrow X_{soln} \cup \{\mathbf{x}_{new}\}$;
return $\mathcal{T}$;

Informed RRT*



Motion primitives as parameterized actions

Definition 1: We define a generic *motion primitive* π as a 6-tuple $\pi(q, \chi, \sigma, T, \xi, C)$ with

- $q \in Q$: the parameters that characterize the primitive;
- χ: the image space of the primitive that corresponds to the image space of the output function of the dynamical system;
- $\sigma : X \times Q \rightarrow \chi$: the **steering function** of the primitive that is a set–valued function based on the system dynamics from the primitive space to the image space; it can be a map on $(0,1)^d$, with $d \geq 2$;
- $T \in \mathbb{R}_{\geq 0}$: the duration of the execution of the primitive;
- $\xi = \rho(t, y), \rho : \mathbb{R}_{\geq 0} \times \chi \rightarrow \Xi = \{0, 1\}$: a trigger that enables the execution of the primitive, where t is the time variable;
- $C : \mathbb{R}_{\geq 0} \times X \times Q \rightarrow \mathbb{R}$: the cost function associated with the primitive.

Example – Locomotion primitives

- $q_L = \emptyset$,
- $\chi_L \ni [x\, y\, \theta\, v]^T$,
- σ_L, an optimization routine, applied on a simplified dynamics, minimizes the time variable t subject to state and control constraints and returns the robot desired trajectory,
- $C_L = t$,
- T_L, is the duration of execution of the steering function σ_L,
- $\xi_L = 0$ until a sample laying in χ_L is added to $\mathcal{T}$.

Motion primitives as parameterized actions

Definition 1: We define a generic *motion primitive* π as a 6-tuple $\pi(q, \chi, \sigma, T, \xi, C)$ with

- $q \in Q$: the parameters that characterize the primitive;
- χ: the image space of the primitive that corresponds to the image space of the output function of the dynamical system;
- $\sigma : X \times Q \to \chi$: the **steering function** of the primitive that is a set–valued function based on the system dynamics from the primitive space to the image space; it can be a map on $(0,1)^d$, with $d \geq 2$;
- $T \in \mathbb{R}_{\geq 0}$: the duration of the execution of the primitive;
- $\xi = \rho(t, y), \rho : \mathbb{R}_{\geq 0} \times \chi \to \Xi = \{0, 1\}$: a trigger that enables the execution of the primitive, where t is the time variable;
- $C : \mathbb{R}_{\geq 0} \times X \times Q \to \mathbb{R}$: the cost function associated with the primitive.

Example – manipulation primitives

- $q_M = o$, where o is the object pose,
- $\chi_M \ni [x\, y\, \tau]^T$,
- σ_M, the inverse kinematics of the robotic arm, giving the joints desired values corresponding to a certain value of o and τ,
- $C_M = t$,
- T_M, is the duration of execution of the steering function σ_M,
- $\xi_M = 1$ when $\|o - r\| \leq \delta$, with r the pose of the robot and $\delta > 0$, otherwise it is 0.

Main idea

- Main idea
  - Use the **motion primitives** for a subsystems as **local planner** in classical sample based planning algorithms to obtain a plan for the whole system
- Basic assumption
  - A motion primitive has an associated control law that stabilize the subsystem it belongs to, while **the control of other sub-systems are null** (i.e., generate steady motion)
- Check for feasibility
  - e.g. using ZMP-condition for humanoid robots

P-Search* algorithm

Algorithm 1: $\mathcal{T} \leftarrow \texttt{P-Search}^*(z_I, z_G)$

Data: $\mathcal{P} = (V, E), z_I, z_G$

Result: $\mathcal{T}$ a tree whose vertices are points $z \in \chi$. Given two vertices $z_i,\ z_j \in \chi_k$ an edge $(z_i,\ z_j)$ is an instantiation of the primitive $\pi_k \in V$ that steers z_i toward z_j in χ_k.

$\mathcal{T} \leftarrow \texttt{InsertNode}(\emptyset, z_I, \mathcal{T})$;

$z_{new} = z_I$;

for $i = 1$ *to* N **do**

- $\mathbb{P}_A \leftarrow \texttt{ActivePrimitives}(z_{new})$;
- $\chi_i \leftarrow \texttt{SamplePrimitive}(\mathbb{P}_A)$;
- $z_{rand} \leftarrow \texttt{Sample}(\chi_i)$;
- $(z_{new}, \mathcal{T}) \leftarrow \texttt{LocalRRT}^*(\chi_i, z_{rand}, \mathcal{T})$;

return $\mathcal{T}$;

Motion primitive available given the current states

Pick up one motion primitives (e.g. choose manipulation primitives)

Specify the motion primitive (e.g., sample a set of joint angles for manipulation motion

P-Search* algorithm

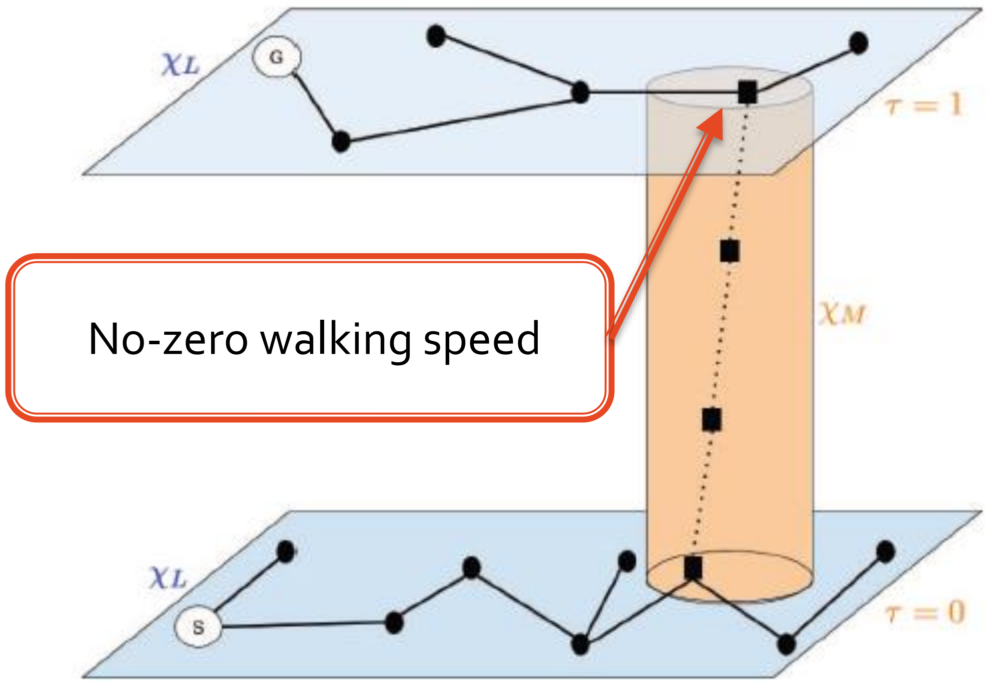
Algorithm 2: $(z_{new}, \mathcal{T}) \leftarrow \texttt{LocalRRT}^*(\chi_k, z, \mathcal{T})$

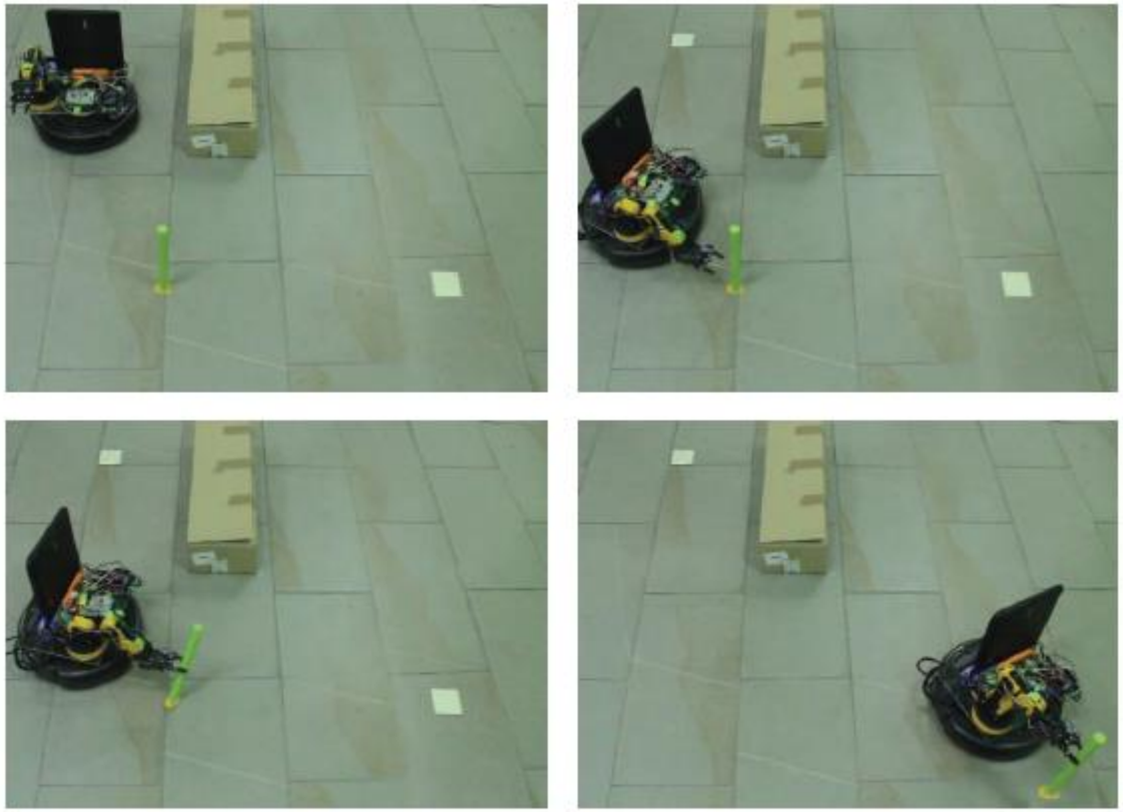
$z_{nearest} \leftarrow \texttt{Nearest}(\chi_k, z, \mathcal{T})$;
$(z_{new}, x_{new}) \leftarrow \texttt{Steer}(z_{nearest}, z)$;
if $\texttt{Unfeasible}(x_{new})$ **then**
    return $(-, \mathcal{T})$;
if $\texttt{ObstacleFree}(x_{new})$ **then**
    $Z_{near} \leftarrow \texttt{Near}(z_{new}, \mathcal{T})$;
    $z_{min} \leftarrow \texttt{ChooseParent}(\mathcal{T}, Z_{near}, z_{nearest}, z_{new})$;
    $\mathcal{T} \leftarrow \texttt{InsertNode}(z_{min}, z_{new}, \mathcal{T})$;
    $\mathcal{T} \leftarrow \texttt{Rewire}(\mathcal{T}, Z_{near}, z_{min}, z_{new})$;
    return $(z_{new}, \mathcal{T})$;
else
    return $(-, \mathcal{T})$;

Check feasibility (e.g., ZMP-condition)

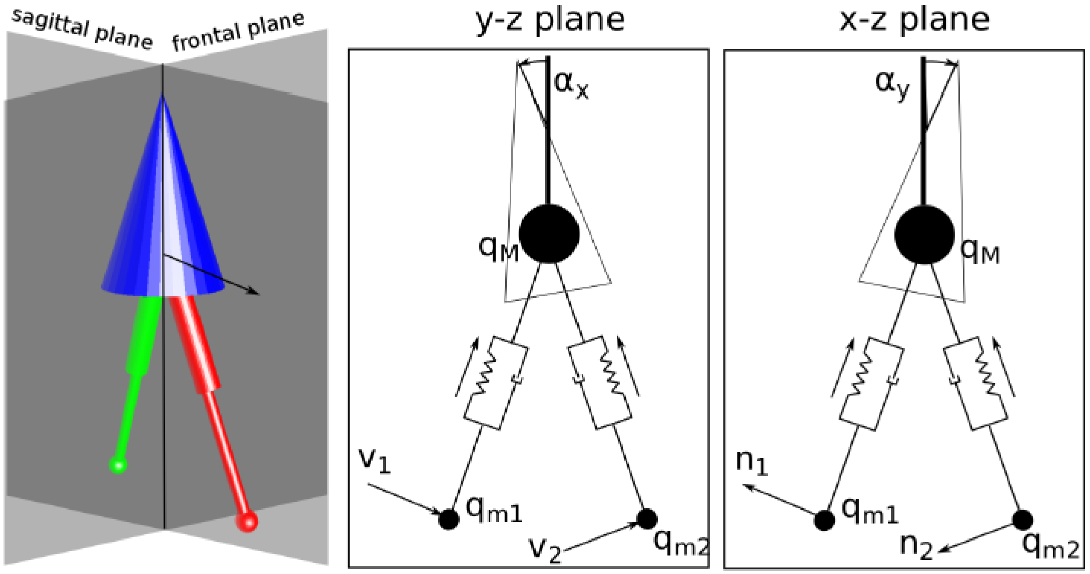
Rewiring

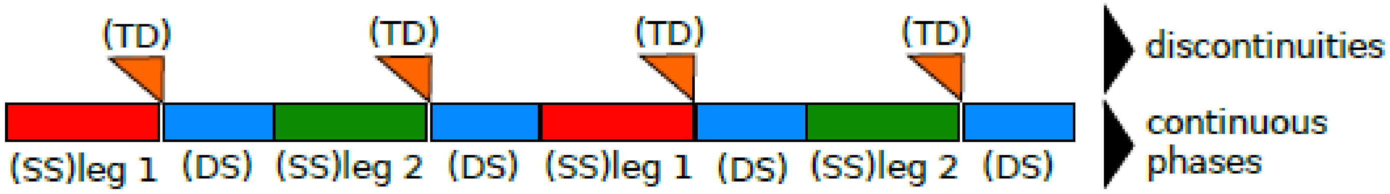
Experiment

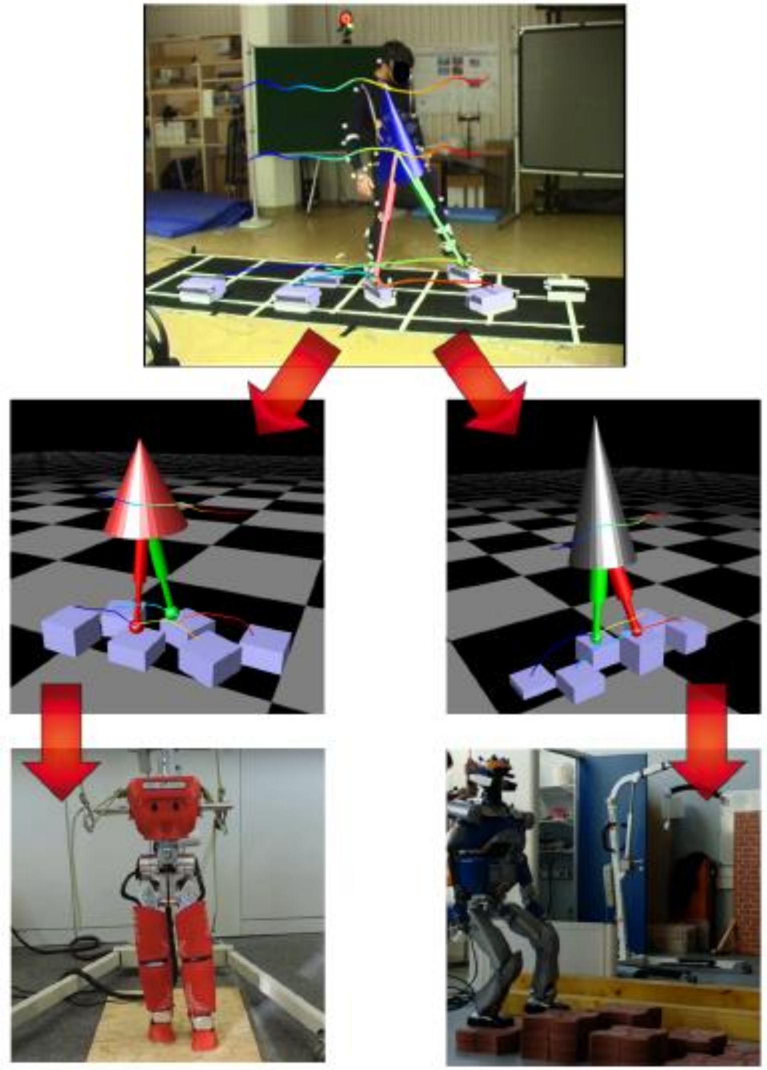




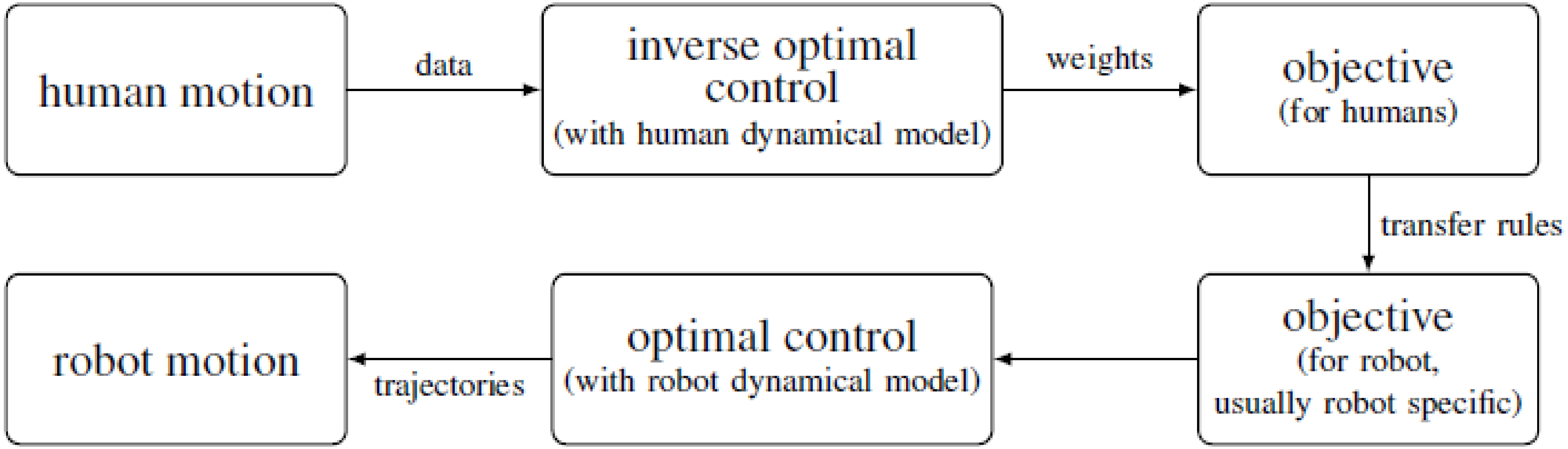
Transfer human walking motion to humanoids [2]







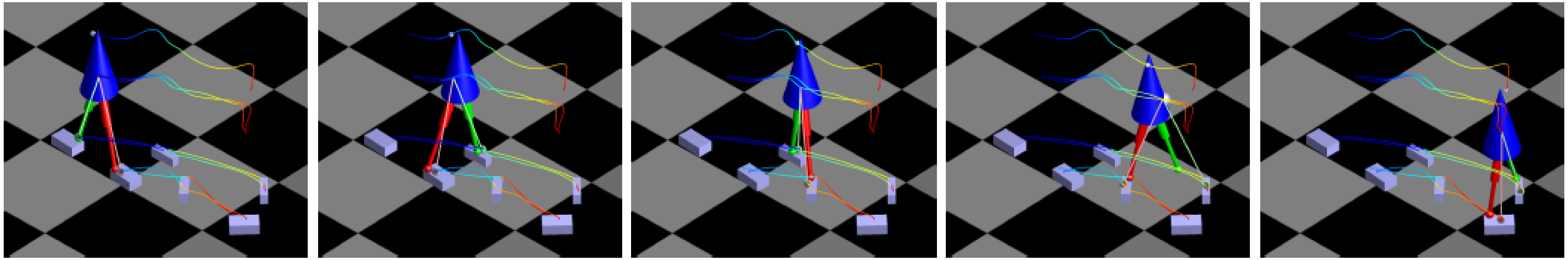
Inverse optimal control



Optimality criteria

- Actuation and energy consumption
  - Minimize actuation in the stance foot, swing foot, torque, hip torque of the swing foot, angular momentum in x and y direction, vertical center of mass oscillations, absolute swing foot velocity
- Motion fitting error
  - Minimize planar distance between foot position at touch down and capture point, periodicity gap in center of mass velocities
- Others
  - Minimize overall single support duration, absolute swing foot velocity at touch down

Demonstration



- Link for demo video:
  - http://orb.iwr.uni-heidelberg.de/ftp/CleverMombaur_IOC_RSS2016

Reference

- [1] Asfour, Tamim, et al. "On the Dualities Between Grasping and Whole-Body Loco-Manipulation Tasks." *Robotics Research*. Springer, Cham, 2018. 305-322.
- [2] Kaiser, Peter, et al. "Validation of whole-body loco-manipulation affordances for pushability and liftability." *Humanoid Robots (Humanoids), 2015 IEEE-RAS 15th International Conference on*. IEEE, 2015.
- [3] Settimi, Alessandro, et al. "Motion primitive based random planning for loco-manipulation tasks." *Humanoid Robots (Humanoids), 2016 IEEE-RAS 16th International Conference on*. IEEE, 2016.
- [4] Clever, Debora, and Katja D. Mombaur. "An Inverse Optimal Control Approach for the Transfer of Human Walking Motions in Constrained Environment to Humanoid Robots." *Robotics: Science and Systems*. 2016.

Extra credit homework – evaluation form