Versatile and Robust Walking in Uneven Terrain

Prof. Dr. Ir. Daniel Rixen

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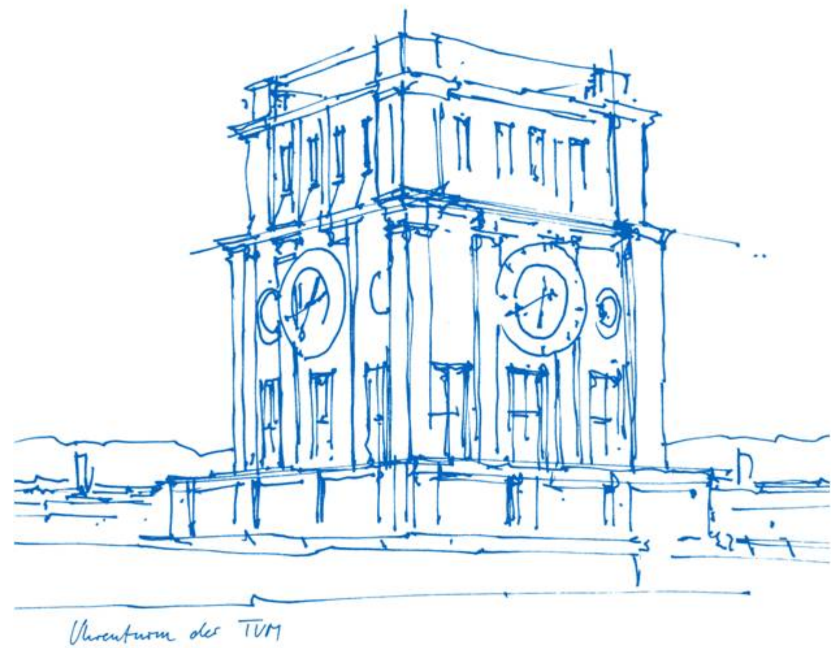
Robert Wittmann

Dr. habil. Ing. Thomas Buschmann

Technical University of Munich

Chair of Applied Mechanics

Garching, 13. January 2016



14:15 – 14:30 **The chair of Applied Mechanics and Lola**
Daniel Rixen

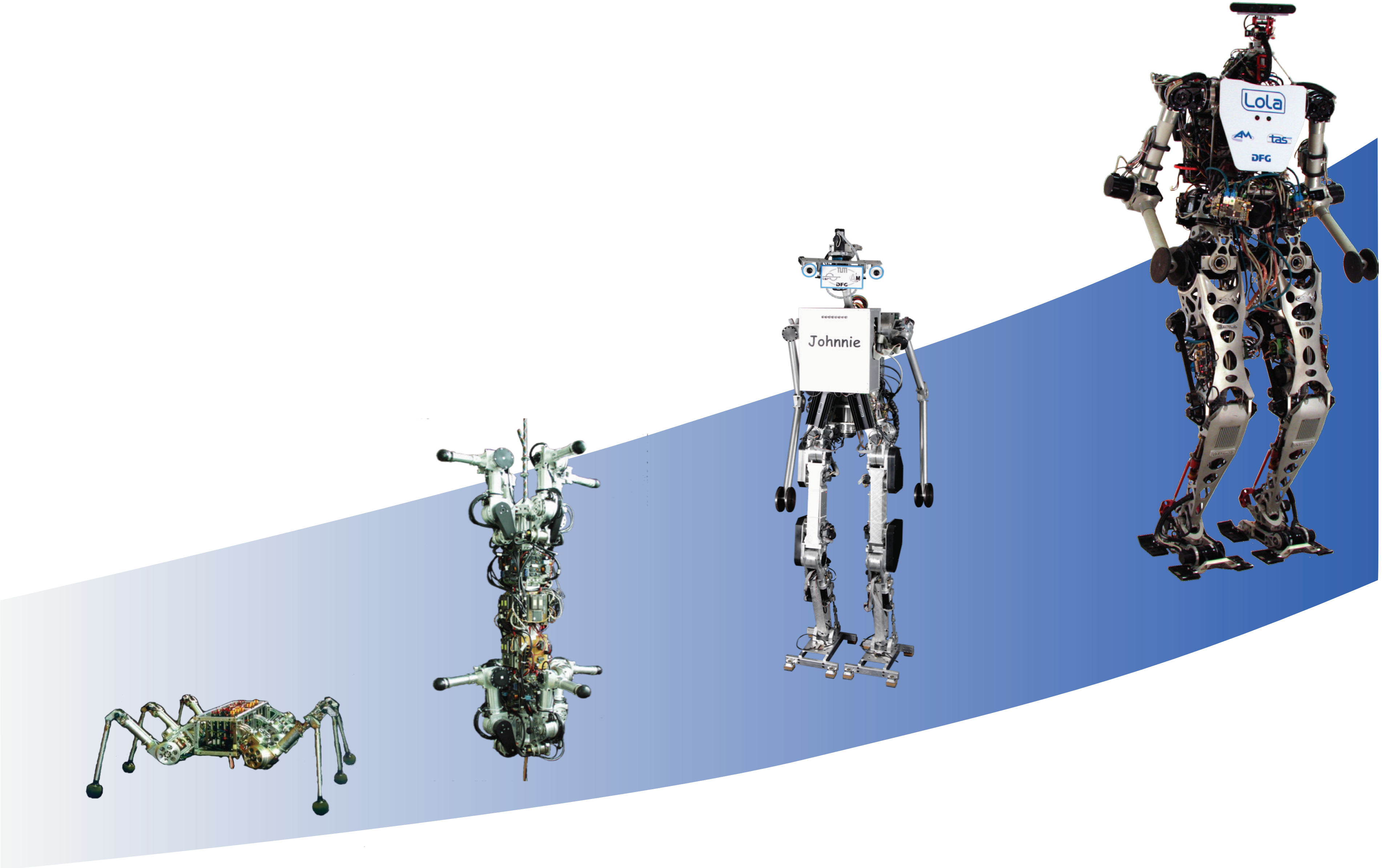
14:30 – 16:00 **Versatile and Robust Walking in unknown Terrain**

- **Environment Modelling & Vision System**
  Daniel Wahrmann (Daad)
- **Navigation & Motion generation**
  Arne Hildebrandt (DFG)

Pause

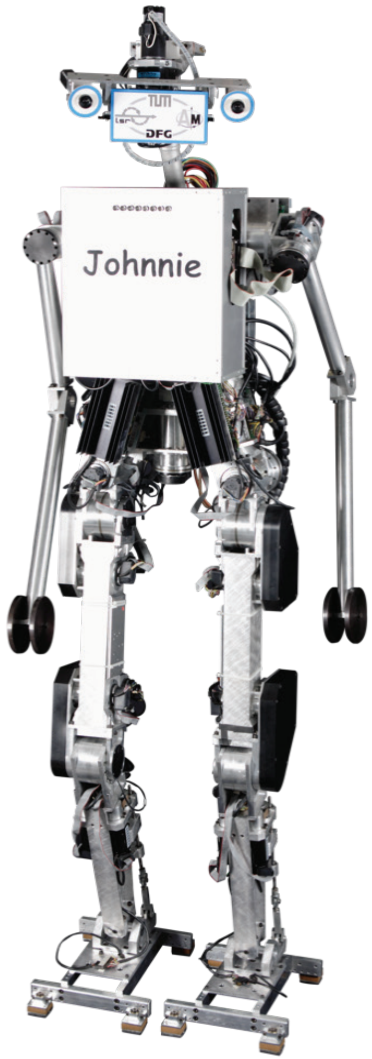
- **Environment Modelling & Vision System**
  Robert Wittmann (DFG)
- **Future Research & outlook**
  Daniel Rixen

16:00 – 17:00 **Lab demonstrations**


Johnnie
Lola
DFG

Humanoider Roboter: „Johnnie“

Prof. F. Pfeiffer



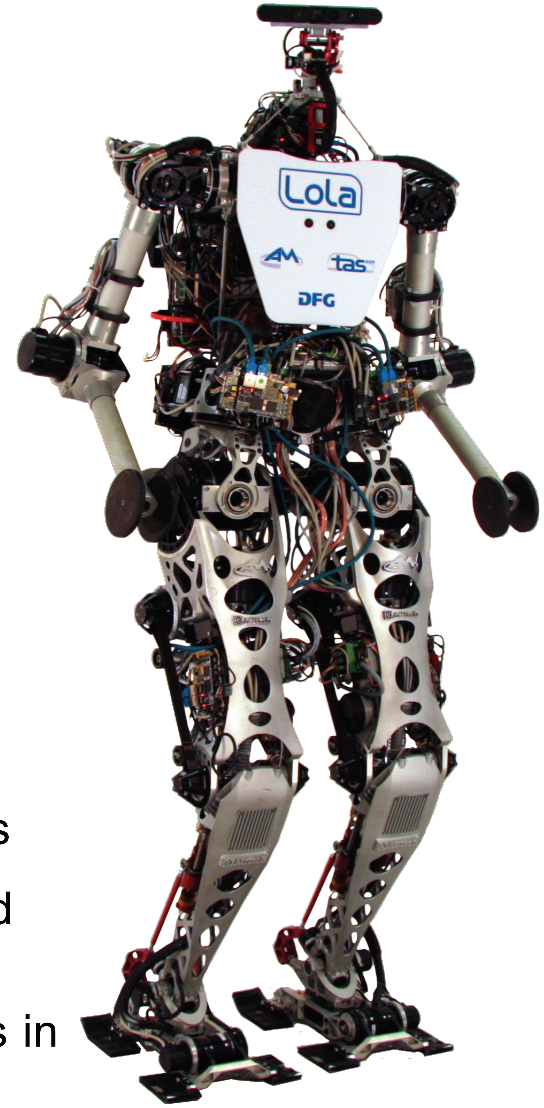
DFG-Schwerpunktprogramms
SPP 1039 - Autonomes Laufen wurde (1997 – 2002)

Dr. Gienger und Dr. Löffler

Humanoider Roboter: „Lola“

Prof. H. Ulbrich

2001 - 2012



DFG-Paketantrag: Natur und Technik intelligenten Laufens
2004-2010 (Sprecher Ansgar Büschges)

- ✓ **Dr. Sebastian Lohmeier:** Design and Realization of a Humanoid Robot for Fast and Autonomous Bipedal Walking
- ✓ **Dr. Thomas Buschmann:** Simulating and Controlling Biped Robots
- ✓ **Dr. Markus Schwienbacher:** Redundancy, Collision Avoidance and Dynamic Trajectory Planning for Humanoid Robots
- ✓ **Dr. Alexander Ewald**: Implementation of Neurobiological Principles in the Walking Control of Humanoid Robots
- ✓ **Dr. Valerio Favot – Dr. Bachmayer:** Electronics and Low-Level Control for Biped Robots

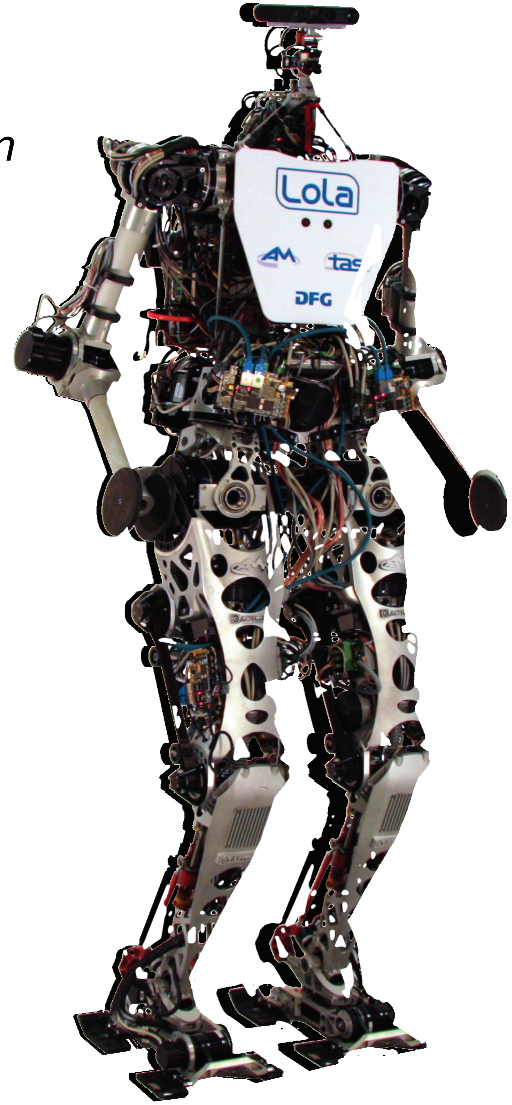
Humanoider Roboter: „Lola“

Dr. T. Buschmann

2012-2014

Prof. dr. D. Rixen

2012 -



DFG- **Flexibles und robustes Gehen in unebenem Gelände**
(2012-2016)

- ✓ **Robert Wittmann:**
  Robustes Gehen auf unebenem Terrain und unter großen Störungen
- ✓ **Arne Hildebrandt:**
  Autonome Navigation humanoider Roboter
- ✓ **Daniel Wahrmann:**
  Autonome Fortbewegung Umgebungsmodellierung
- ✓ **Felix Sygulla:**
  Robusteres Gehen auf unerkanntem unebenem Gelände mit Hilfe von taktilem Feedback
- ✓ **Philipp Seiwald**

Results are published in:

R. Wittmann, A.-C. Hildebrandt, D. Wahrmann, D. Rixen and T. Buschmann, “Model-Based Predictive Bipedal Walking Stabilization”, in *IEEE-RAS International Conference on Humanoids Robots*, 2016

A.-C. Hildebrandt, M. Demmeler, R. Wittmann, D. Wahrmann, F. Sygulla, D. Rixen and T. Buschmann, “Real-Time Predictive Kinematic Evaluation and Optimization for Biped Robots”, in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015

R. Wittmann and D. Rixen, “A Prediction Model for State Observation and Model Predictive Control of Biped Robots”, in *Proc. Appl. Math. Mech., Wiley-Blackwell*, 2016

D. Wahrmann, A.-C. Hildebrandt, R. Wittmann, F. Sygulla, D. Rixen and T. Buschmann, “Fast Object Approximation for Real-Time 3D Obstacle Avoidance with Biped Robots”, in *IEEE International Conference on Advanced Intelligent Mechatronics*, 2016

A.-C. Hildebrandt, C. Schuetz, D. Wahrmann, R. Wittmann and D. Rixen, “A Flexible Robotic Framework for Autonomous Manufacturing Processes: Report from the European Robotics Challenge Stage 1”, in *IEEE International Conference on Autonomous Robot Systems and Competitions*, 2016

A.-C. Hildebrandt, D. Wahrmann, R. Wittmann, D. Rixen and T. Buschmann, “Real-Time Pattern Generation Among Obstacles for Biped Robots”, in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015

R. Wittmann, A.-C. Hildebrandt, D. Wahrmann, T. Buschmann and D. Rixen, “State Estimation for Biped Robots Using Multibody Dynamics”, in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015

R. Wittmann, A.-C. Hildebrandt, D. Wahrmann, D. Rixen and T. Buschmann, “Real-Time Nonlinear Model Predictive Footstep Optimization for Biped Robots”, in *IEEE-RAS International Conference on Humanoids Robots*, 2015

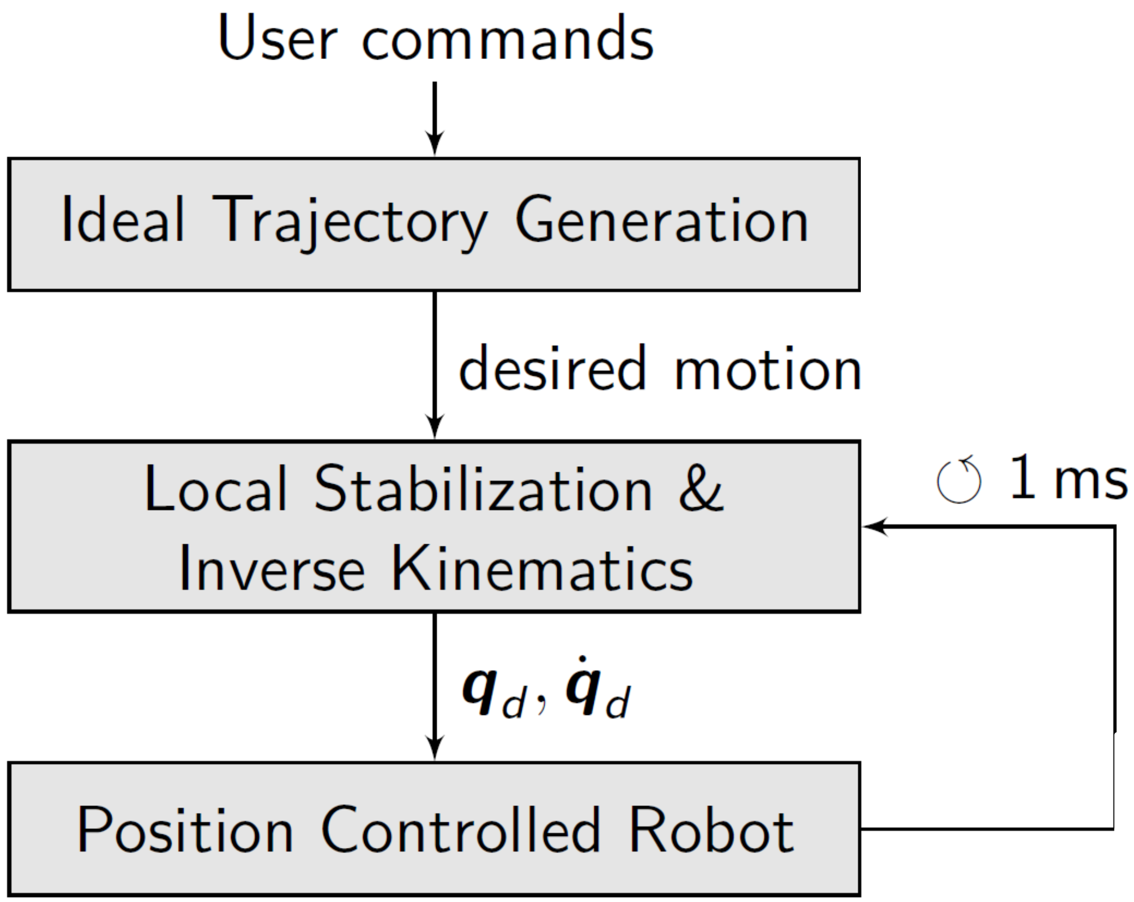
R. Wittmann, A.-C. Hildebrandt, A. Ewald and T. Buschmann, “An Estimation Model for Footstep Modifications of Biped Robots”, in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2014

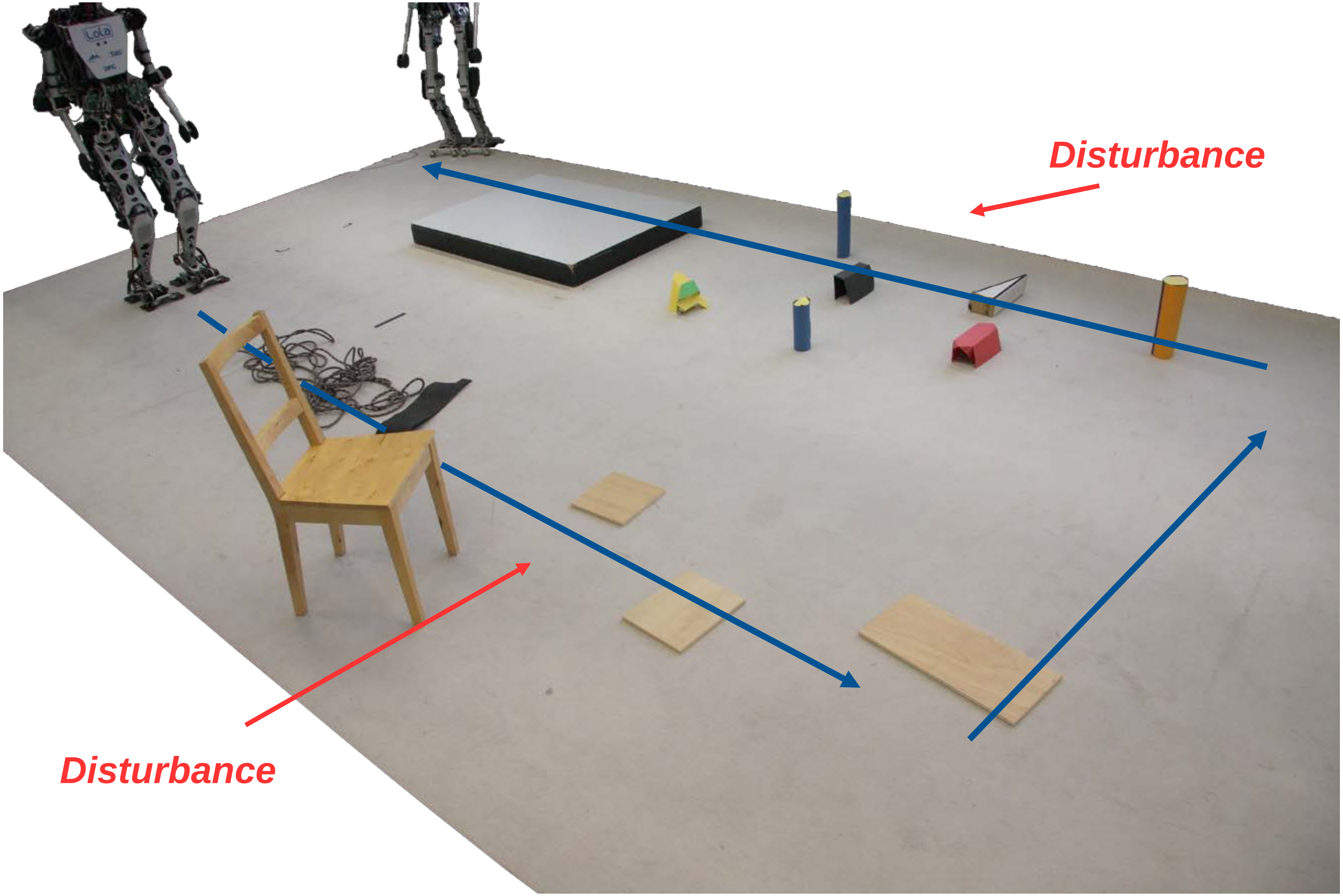
A.-C. Hildebrandt, R. Wittmann, D. Wahrmann, A. Ewald and T. Buschmann, “Real-Time 3D Collision Avoidance for Biped Robots”, in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2014

http://www.lake-skadar.com/

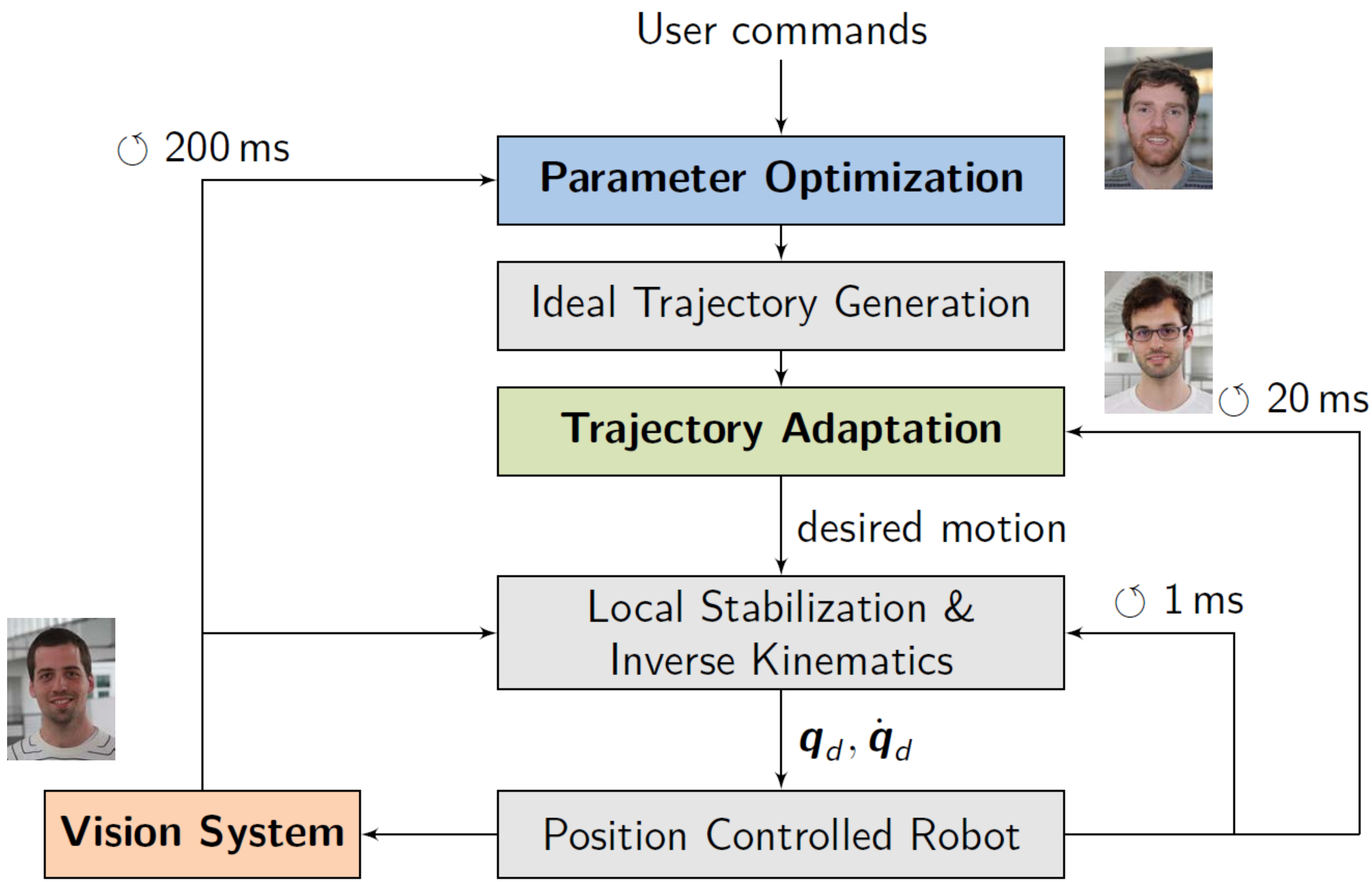
http://www.touristmaker.com/

Real-Time Control

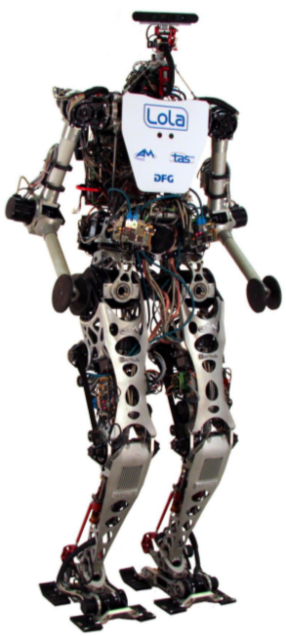


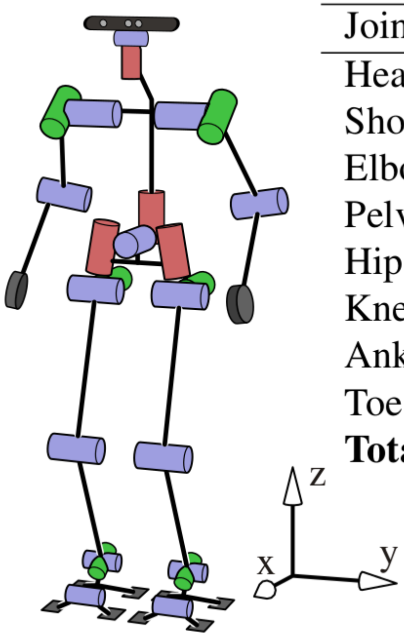

Disturbance
Disturbance

Real-Time Autonomous Navigation



The Humanoid Robot “Lola”

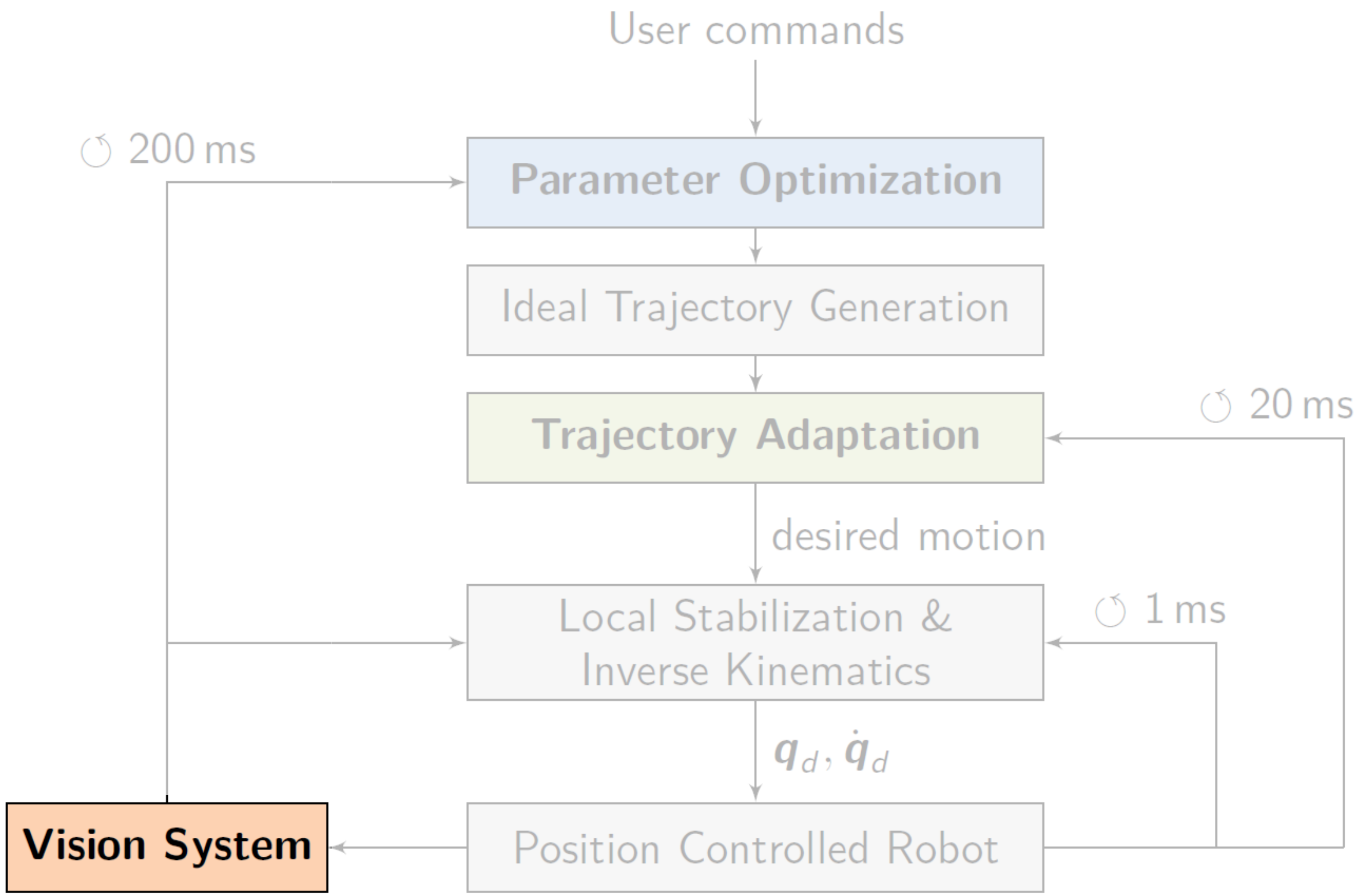




Joint	DoF
Head	2
Shoulder	2
Elbow	1
Pelvis	2
Hip	3
Knee	1
Ankle	2
Toe	1
Total	**24**

- 60 kg
- 1,8 m
- Asus Xtion PRO LIVE
- 2 Intel i7 Computers
  - Control (QNX)
  - Vision System (Linux)

Real-Time Autonomous Navigation



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Introduction and Motivation

Environment Modeling

Vision System

Navigation and Motion Generation

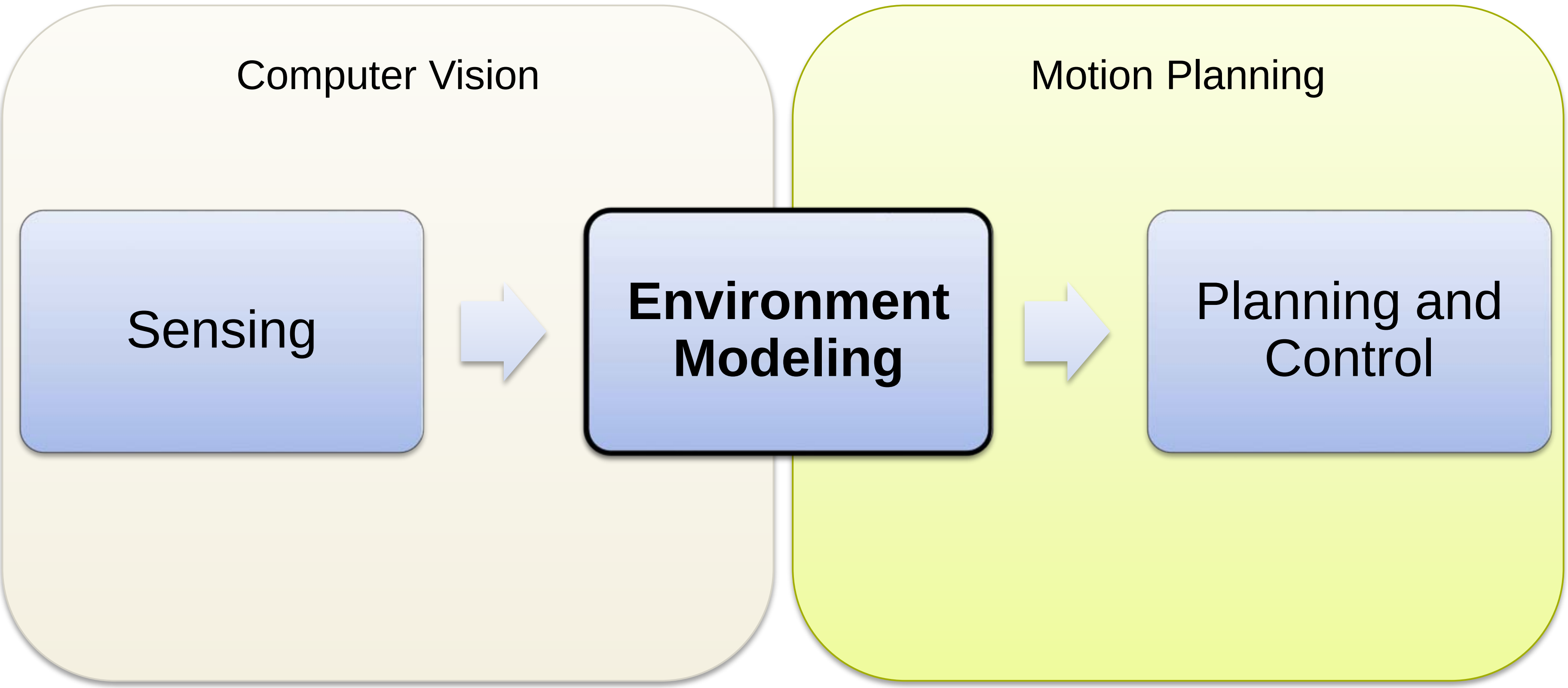
Stabilization

Results

Limitations

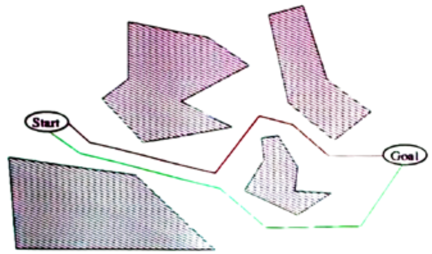
Perspectives

Autonomous Navigation in Unknown Environments



Autonomous Navigation: Examples

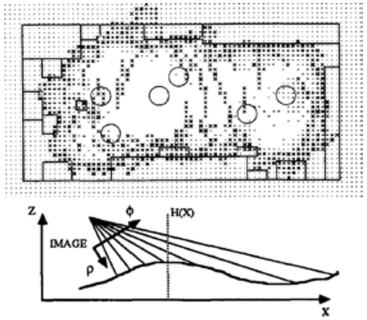
2D-Representation



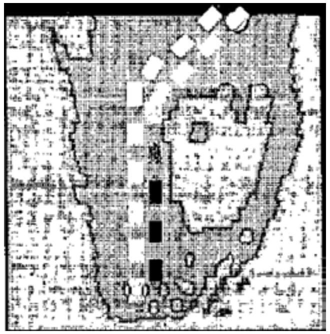
A* - Search Algorithm
(Hart et al. 1968)

Shakey the Robot
(Credit: SRI International)

2,5D-Representation

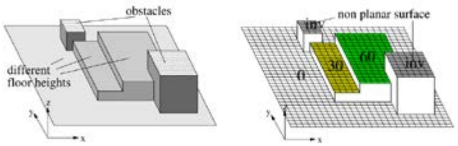


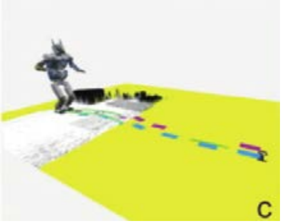
“Height Maps”
(Moravec et al. 1985,
Herbert et al. 1989)



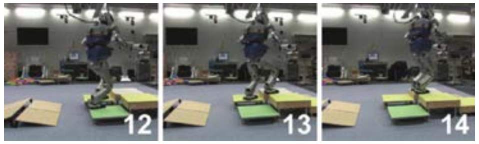
Humanoid Navigation
(Kagami et al. 2003)

Segmented 2,5D-Representation



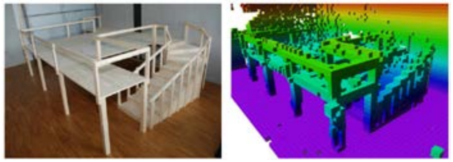


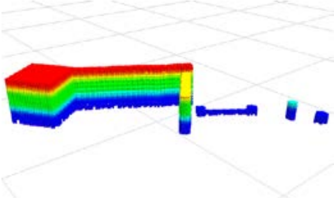
Sony Qrio
(Gutmann et al. 2005)

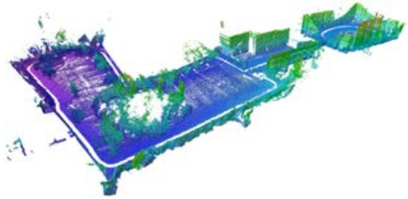


HRP 2
(Nishiwaki et al. 2012)

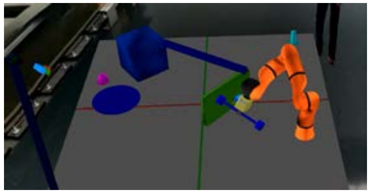
3D-Representation





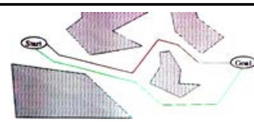
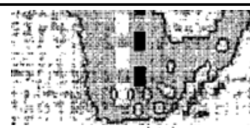
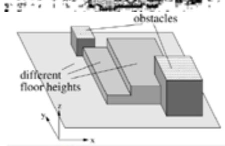
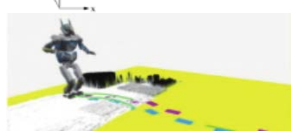
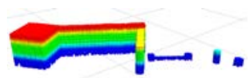


“Octomaps”
(Wurm et al. 2010)

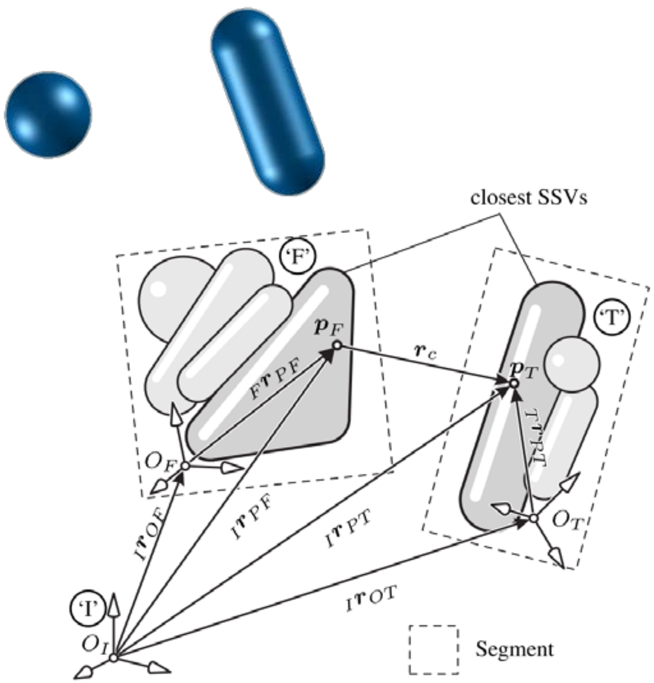


EuRoC
(ICARSC 2016)

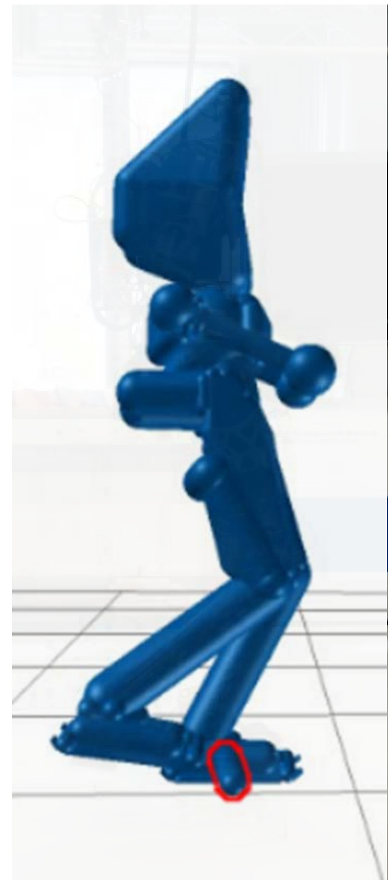
Environment Modeling

Art	Beispiel		Planung und Kollisionsvermeidung	Dynamische Umgebung?
2D	Shakey			~
2,5D	H7			~
	Qrio			~
	HRP 2			×
	…			
3D				✓
	Octomaps			×

Collision Model

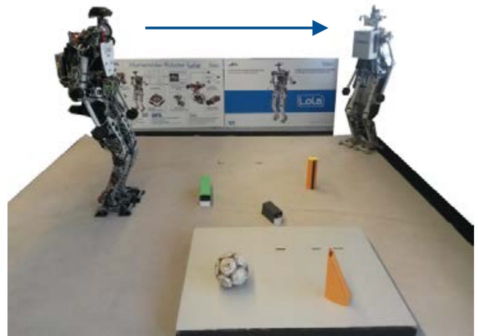


Swept-Sphere-Volumes (SSVs)
(ICRA 2011)

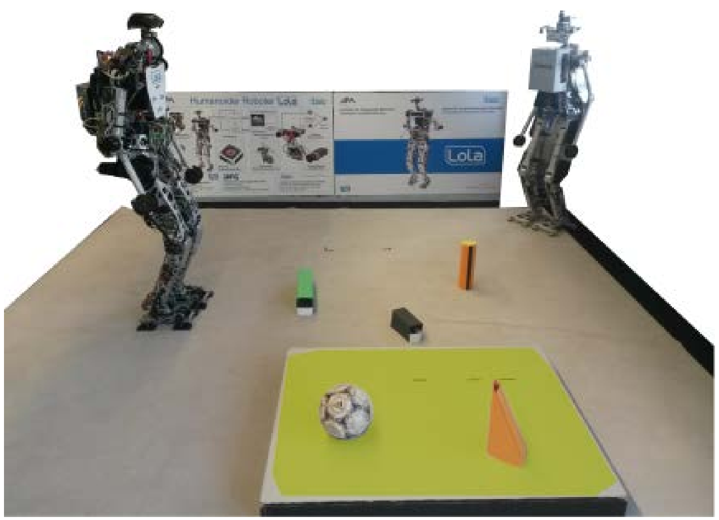


Obstacle Avoidance
(IROS 2015, AIM 2016)

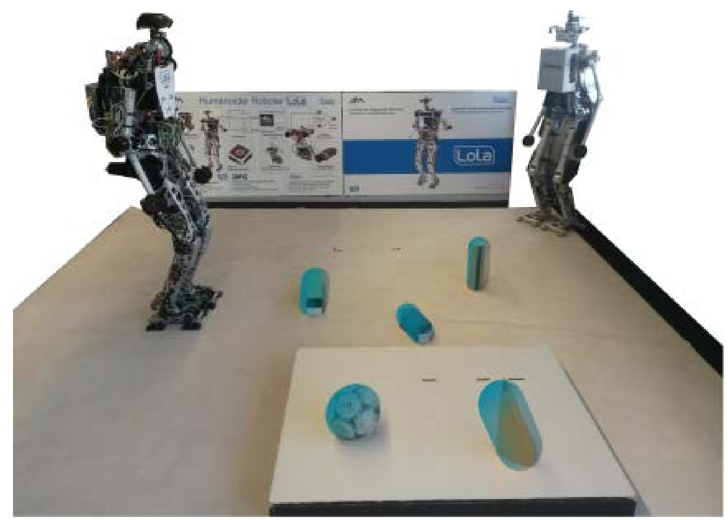
Environment Model



Walkable Surfaces



Collision Objects



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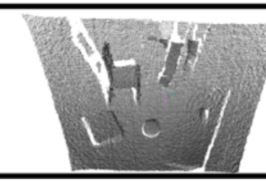
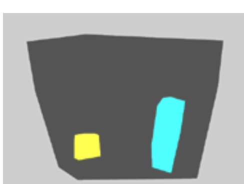


Surface Approximation

- Segmentation
- Clustering
- Approximation
- Tracking

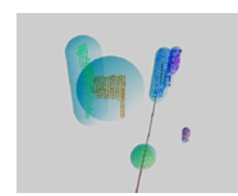


Plane Recognition

not-so-RANSAC

Obstacle Approximation

- Segmentation
- Clustering
- Approximation
- Tracking

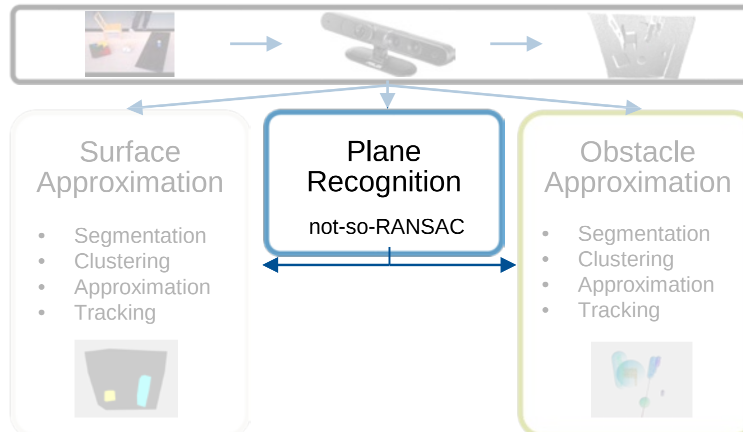


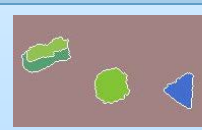
http://github.com/am-lola/lepp3

Vision System

Plane Recognition

Recognize walkable surfaces from the scenario.



Input	Method	Output	Time/Frame [ms]	Proprieties
	Depth-Map		90-110	easy, inexact, difficulty with multiple surfaces
	Normal-Based		800-1100	robust, slow, problem with far-away objects
	RANSAC		50-70	fast, multiple surfaces, parameter-sensible
	…			

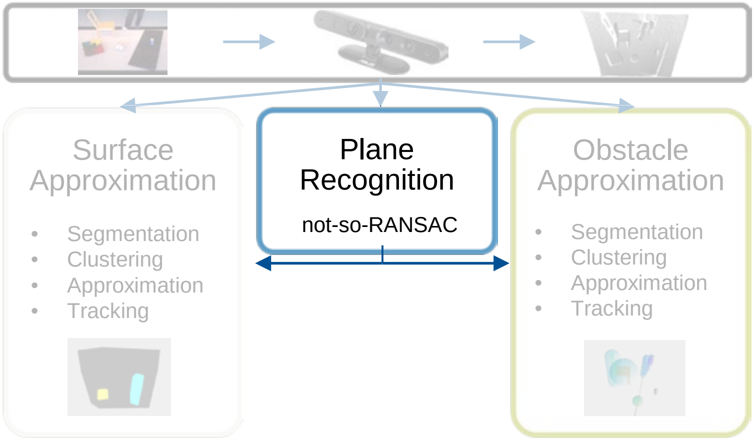
Vision System

RANdom SAmple Consensus (RANSAC)

Iterative test of plane parameters

$\boldsymbol{a}x + \boldsymbol{b}y + \boldsymbol{c}z + \boldsymbol{d} = 0$

until enough inliers are found



Generates a list of plane parameters

a_1, b_1, c_1, d_1

a_2, b_2, c_2, d_2

...

a_i, b_i, c_i, d_i

Modifications:

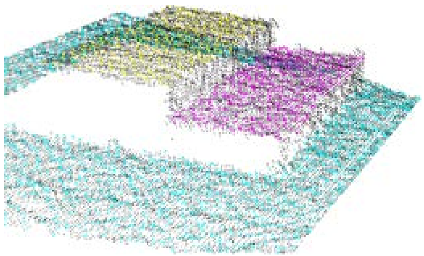
not-so-RANSAC

Initialized with known planes

Classification

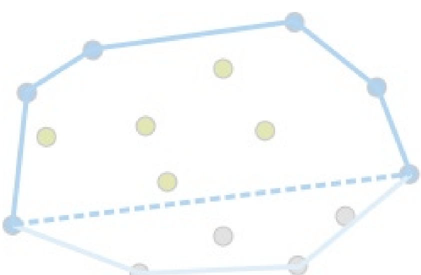
Separate clusters based on inclination

Vision System



Euclidean Clustering

- Classification based on plane inclination

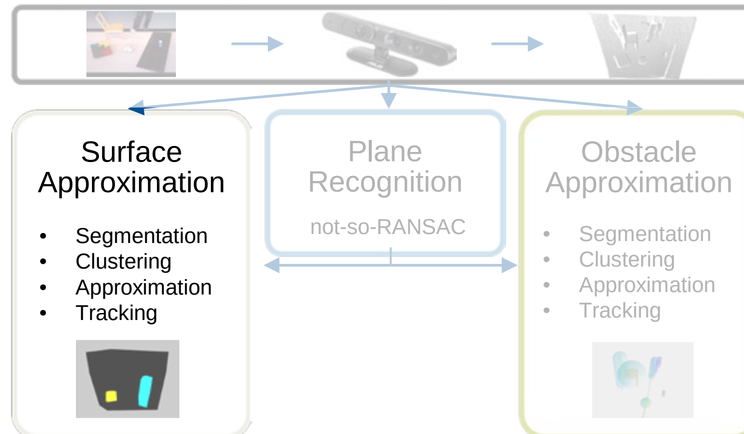


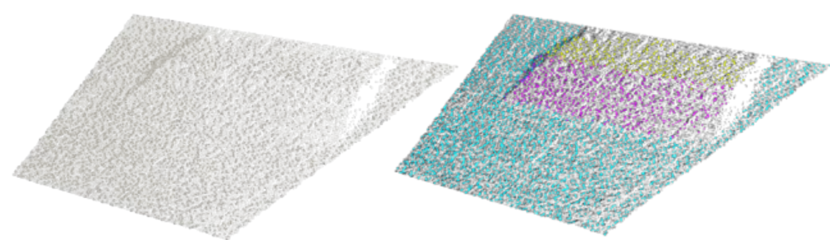
Polygon Approximation

- Quickhull Algorithm
- Iterative reduction to a n-sided polygon

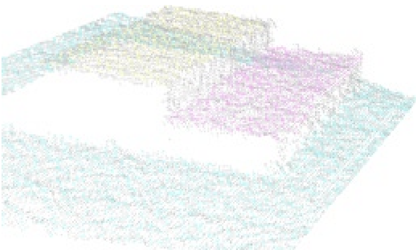
Polygon Tracking

- Geometric low-pass filter

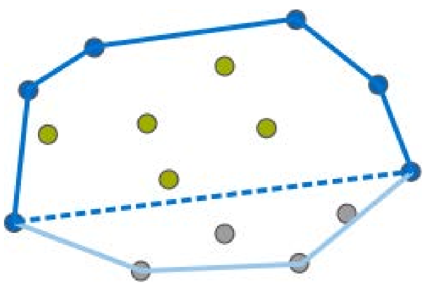




Vision System



Euclidean Clustering
- Classification based on plane inclination



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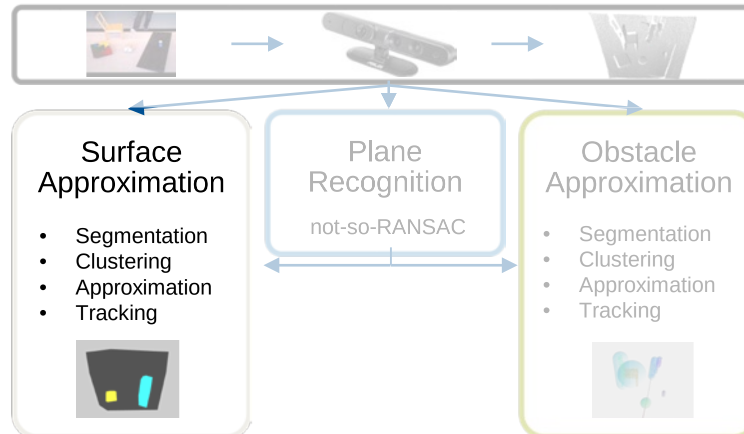
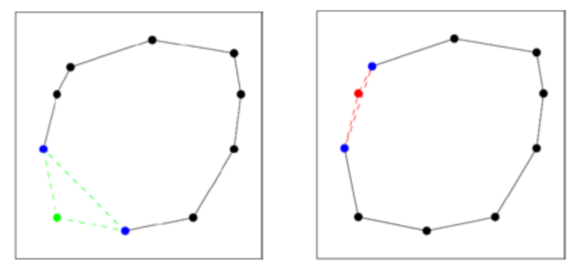
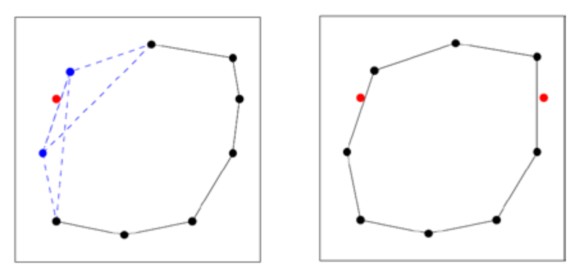
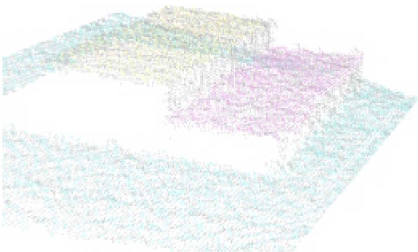


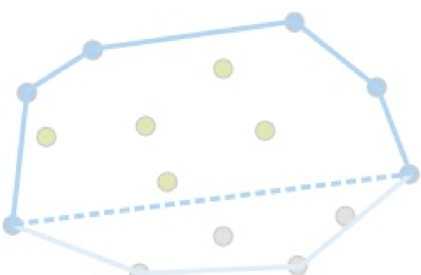




Vision System



Euclidean Clustering
- Classification based on plane inclination



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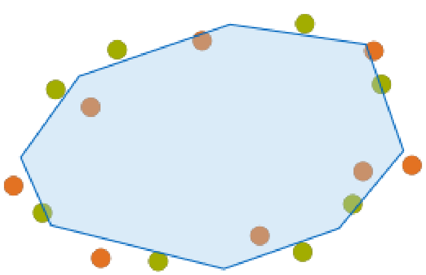
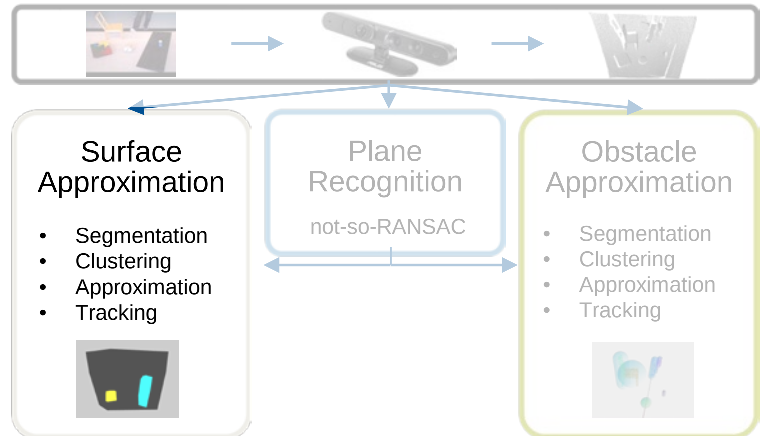
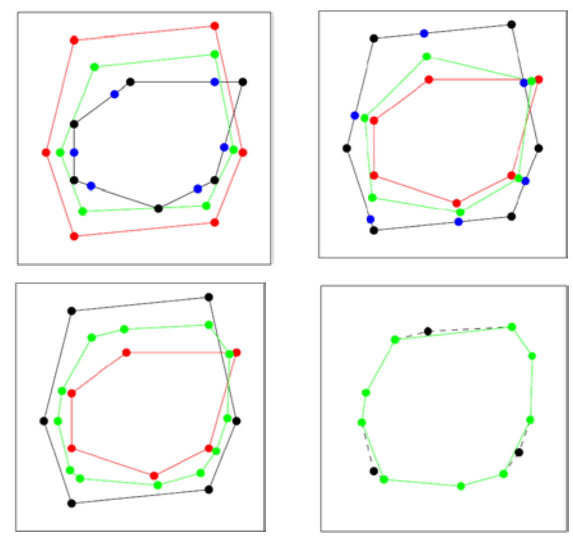
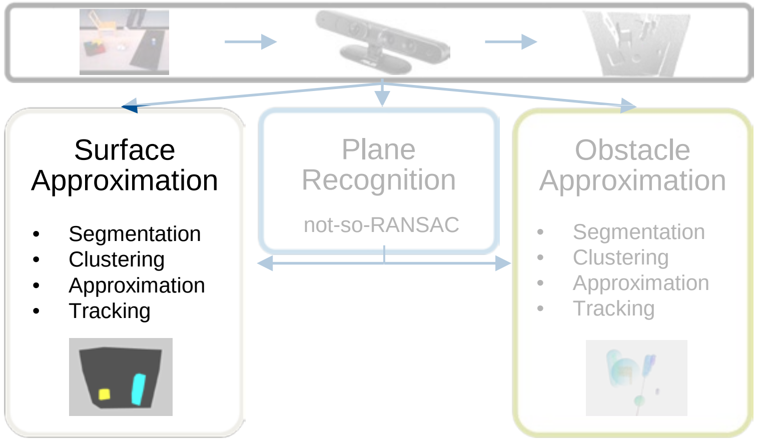


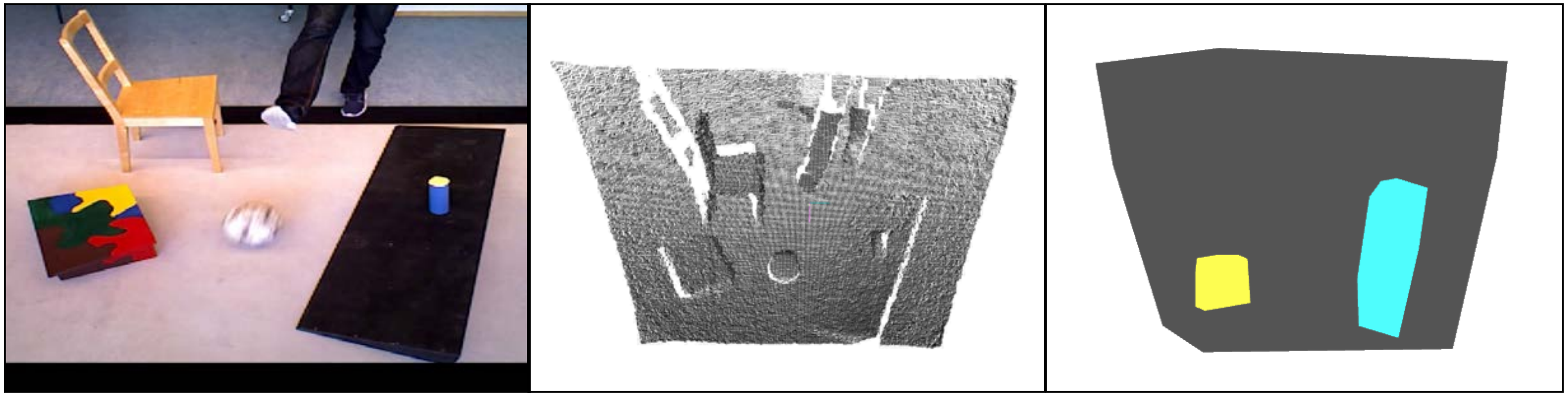
Polygon Tracking
- Geometric low-pass filter





Vision System



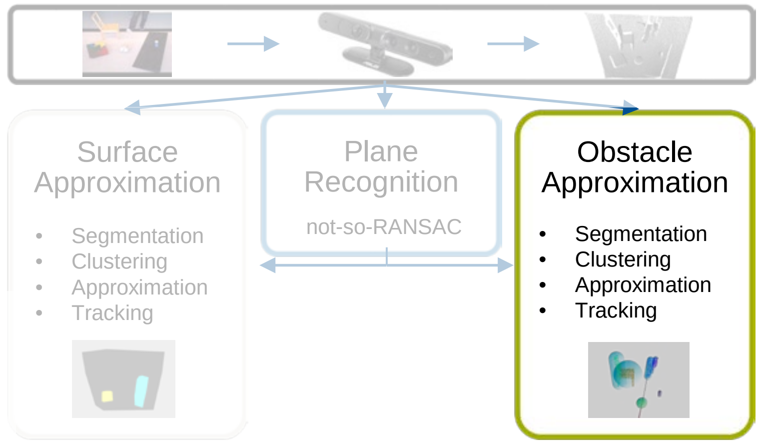


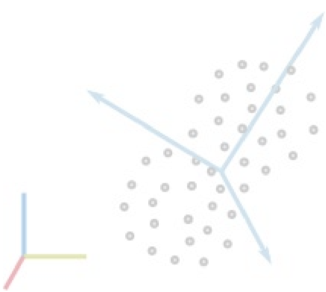
Vision System

Gaussian Clustering

„Gaussian Mixture Models“

Probabilistic fit of a 3D normal distribution





„Swept-Sphere-Volumes“ (SSVs) Approximation

Inertia tensor analysis (PAD)

Main moments of inertia

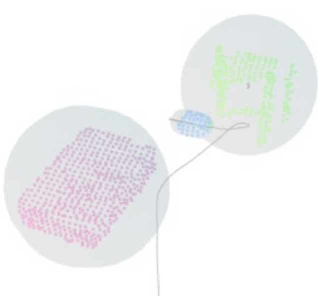
GMM: *K* gaussians with the following form:

$$p(x|\theta) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k)$$

Expectation Step (iteration through each point x_i and Gaussian k): “responsibility”

Maximization Step (iteration through each Gaussian k): new mean μ_k^{new}, covariance Σ_k^{mle} and mixing coefficient π_k^{new}

Regularization: add a low-pass filter to the covariance: $\Sigma_k^{new} = \lambda\Sigma_k + (1-\lambda)\Sigma_k^{mle}$



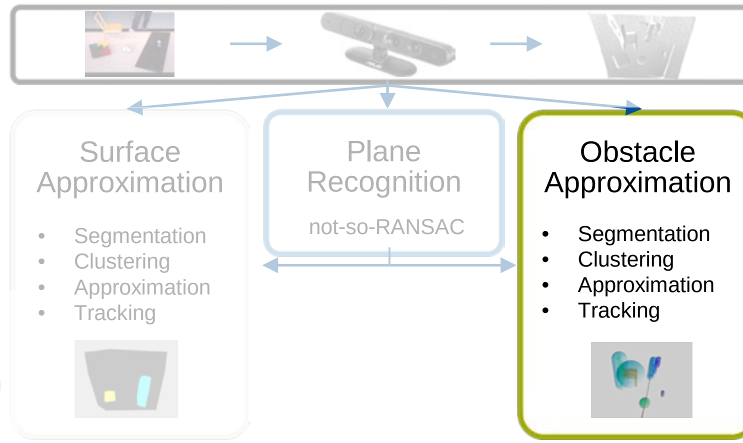
Obstacle-Tracking

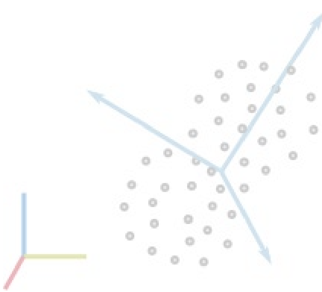
Kalman-Filter on the obstacle’s centroid with constant $\dot{x}$ and Gaussian noise on x and $\dot{x}$

Vision System

Gaussian Clustering

- „Gaussian Mixture Models“
- Probabilistic fit of a 3D normal distribution





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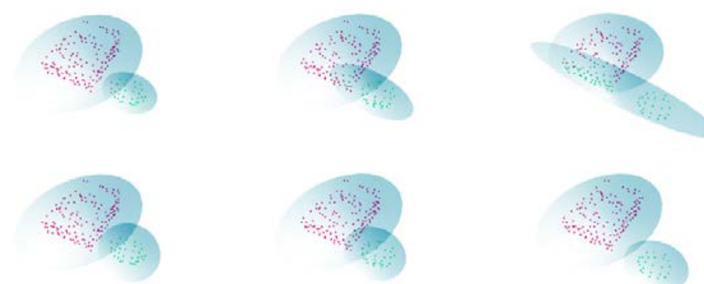

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Vision System

Gaussian Clustering
- „Gaussian Mixture Models“
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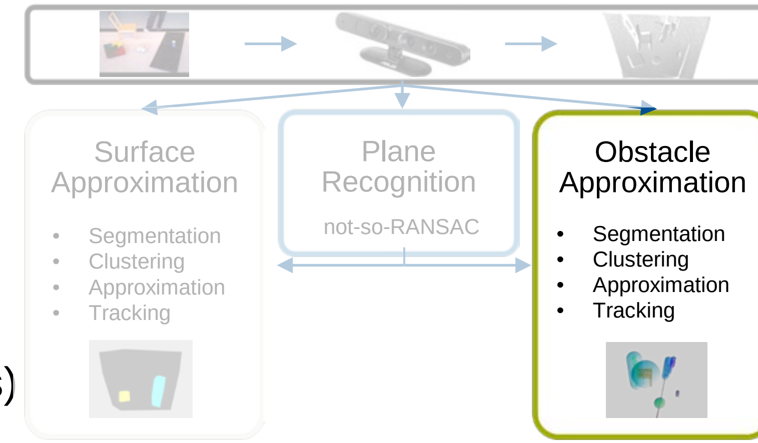
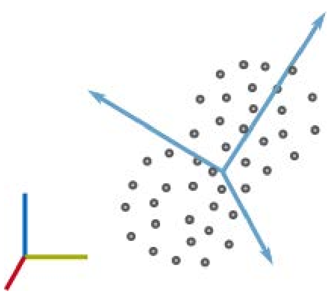




„Swept-Sphere-Volumes“ (SSVs) Approximation
- Inertia tensor analysis (PAD)
- Main moments of inertia

Inertia Matrix I

eigenvalues $I_{max} \geq I_{mid} \geq I_{min}$

Geometric invariants:

$$\xi_1 = \frac{I_{min}}{I_{max}} \qquad \xi_2 = \frac{I_{mid}}{I_{max}}$$

Point-SSV: $I_{max} \cong I_{mid} \cong I_{min}$

$\rightarrow \boldsymbol{\xi_1 \cong \xi_2 \cong 1}$

Line-SSV: $I_{max} \gg I_{mid} \cong I_{min}$

$\rightarrow \boldsymbol{\xi_1 < \xi_2 \cong 1}$

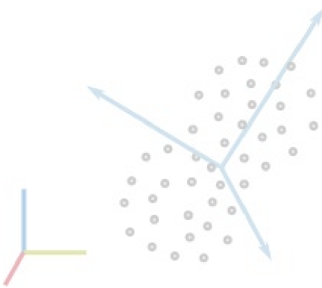
Obstacle-Tracking
- Kalman-Filter on the obstacle’s centroid with constant $\dot{x}$ and Gaussian noise on x and $\dot{x}$

Vision System

Gaussian Clustering

„Gaussian Mixture Models“

Probabilistic fit of a 3D normal distribution



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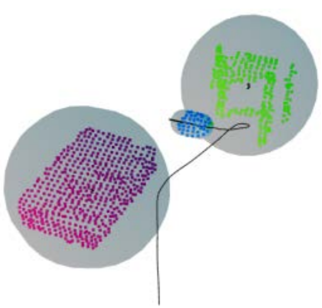

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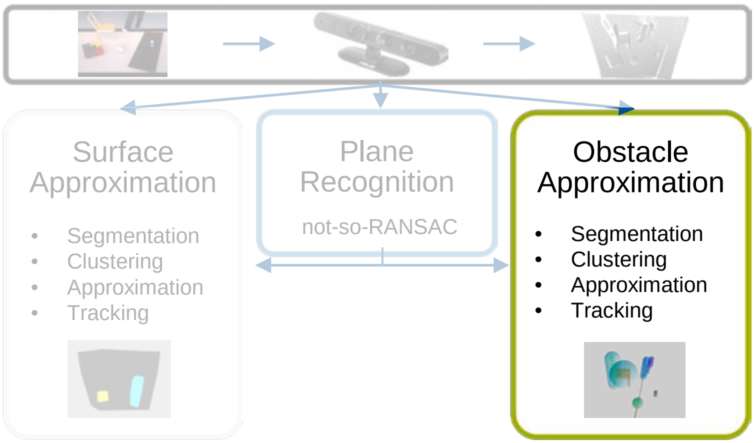
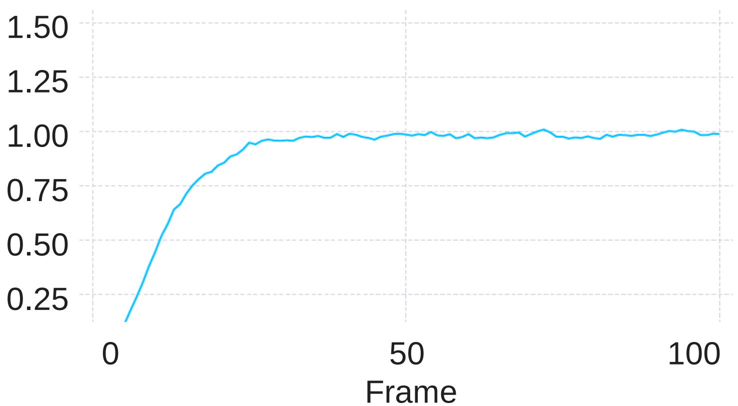
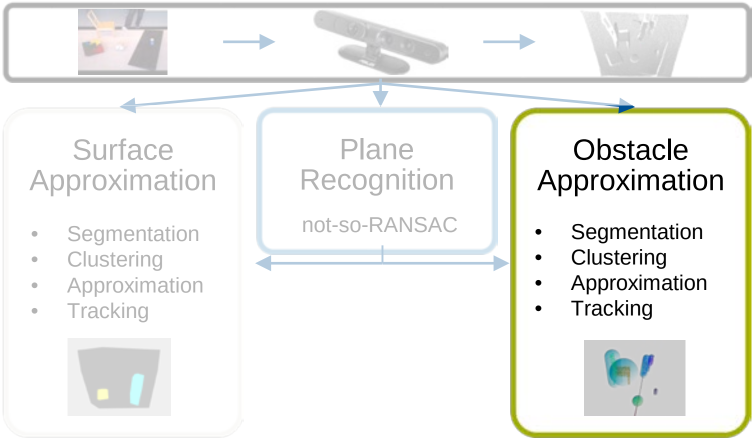
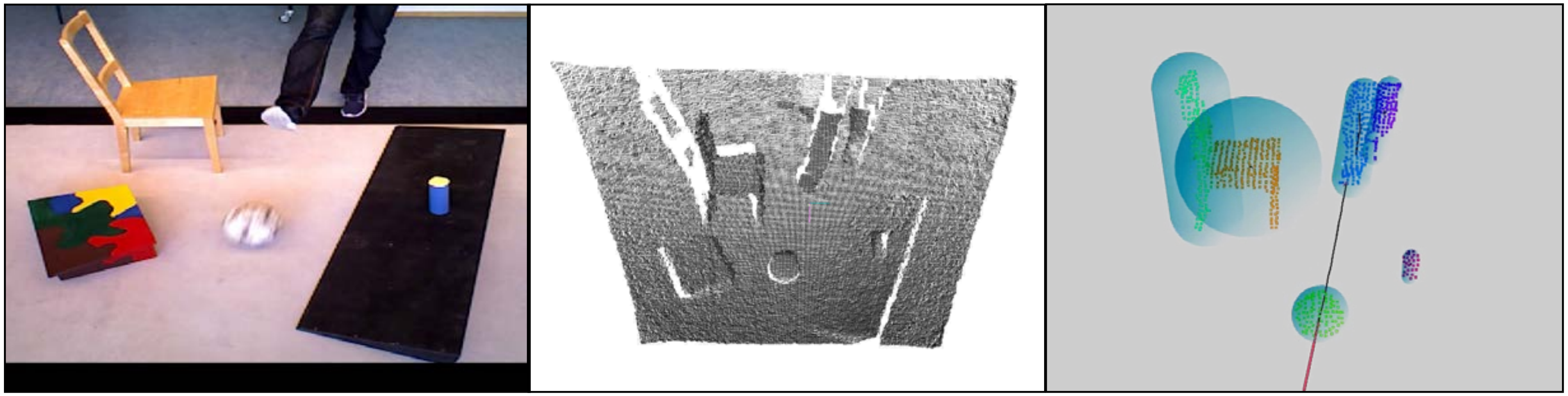




Vision System

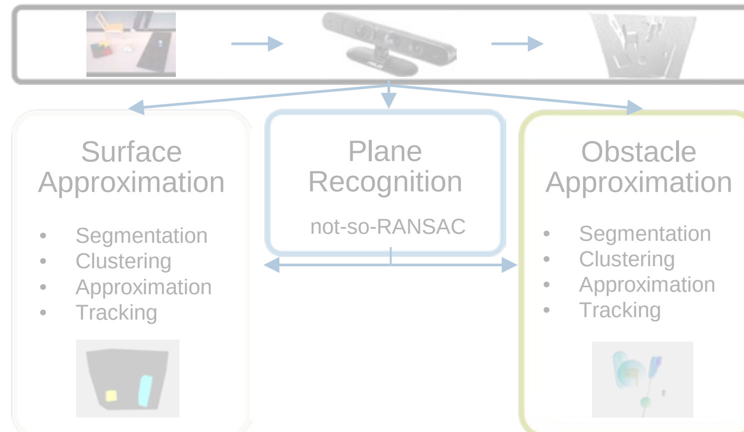


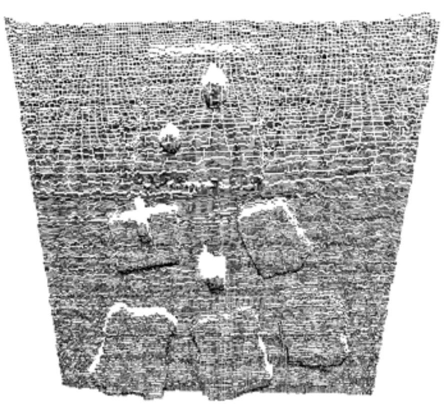


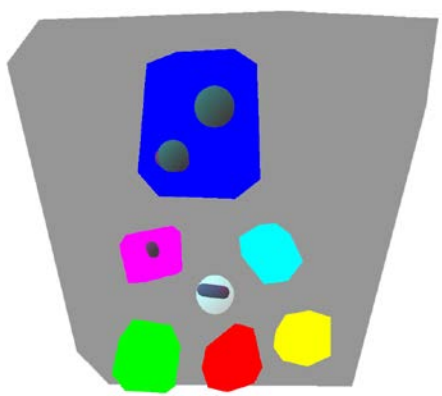
Vision System

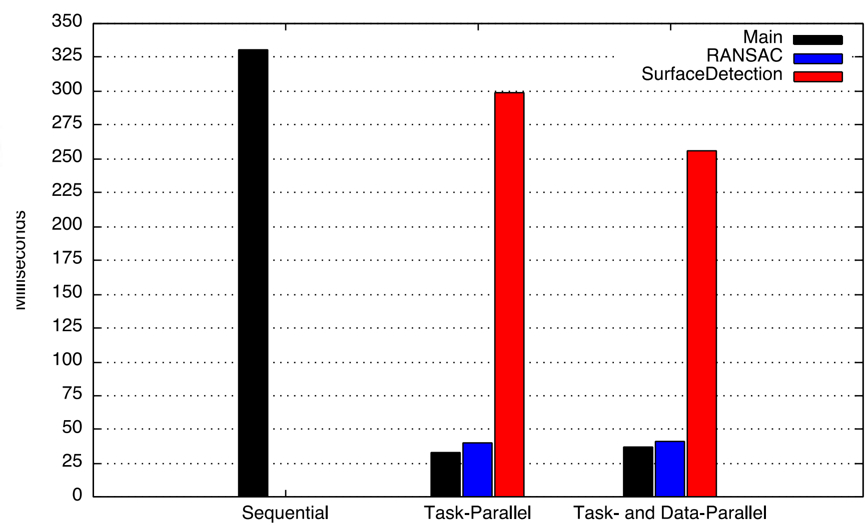
Vision System

Parallel Processes









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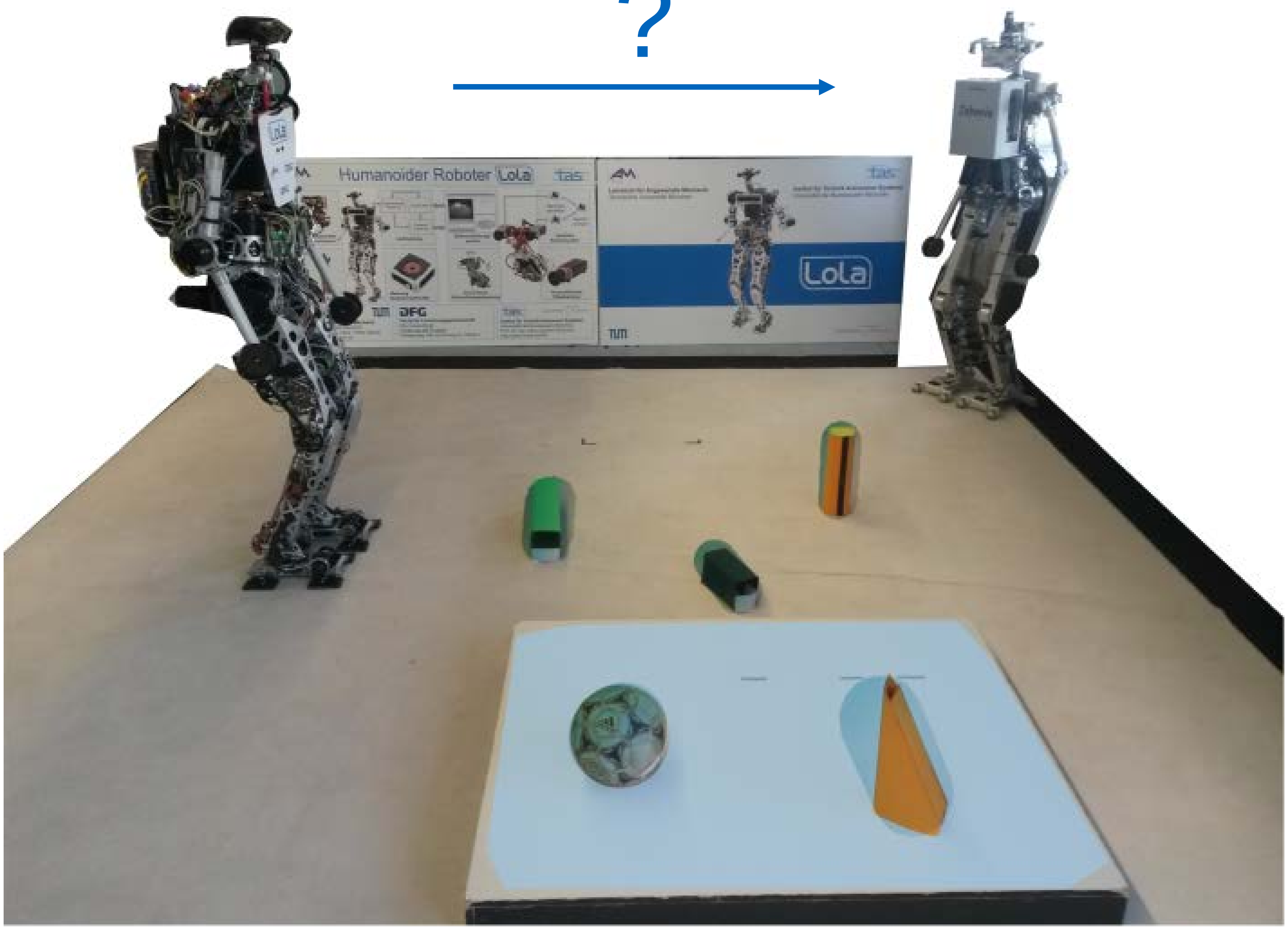
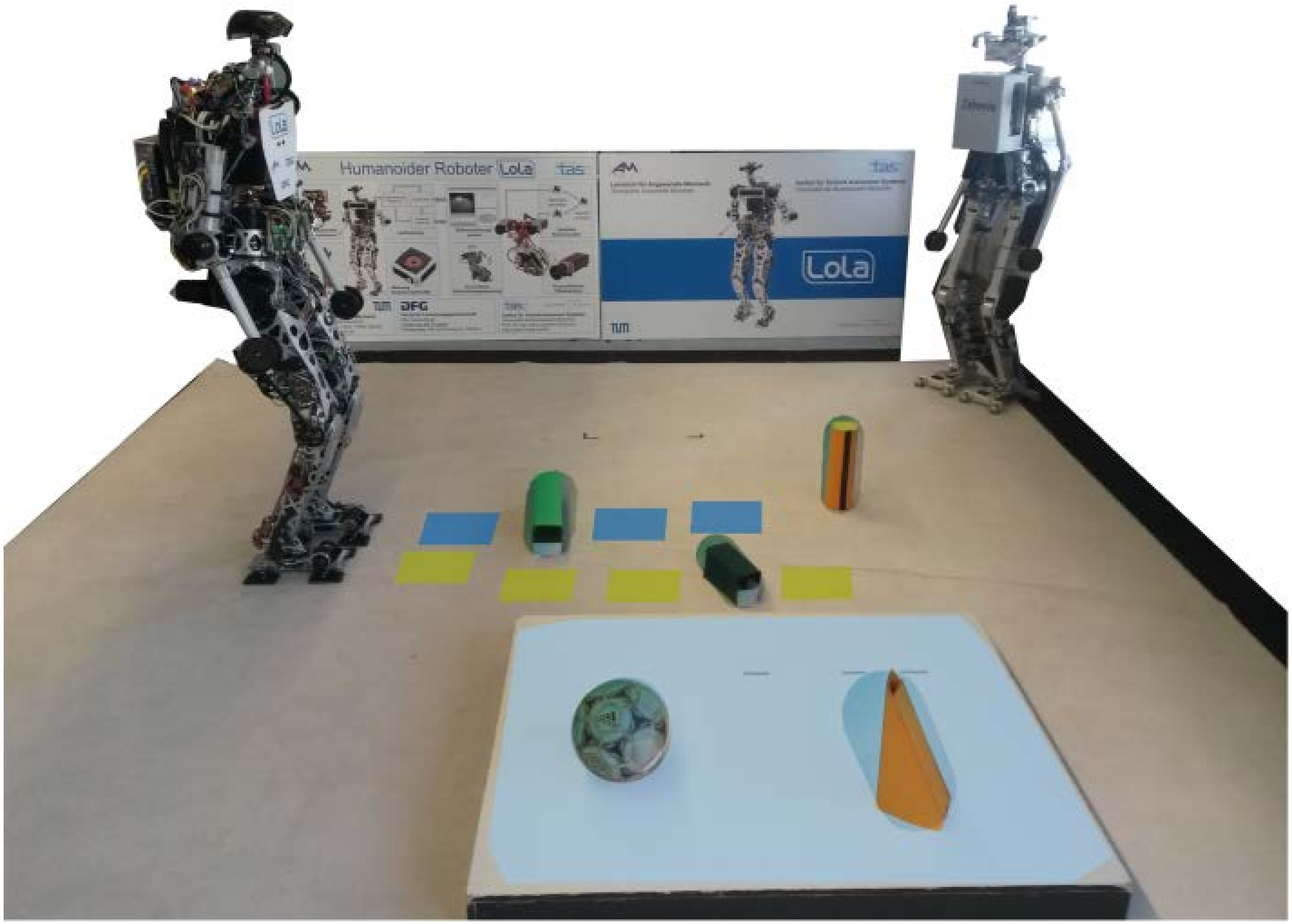
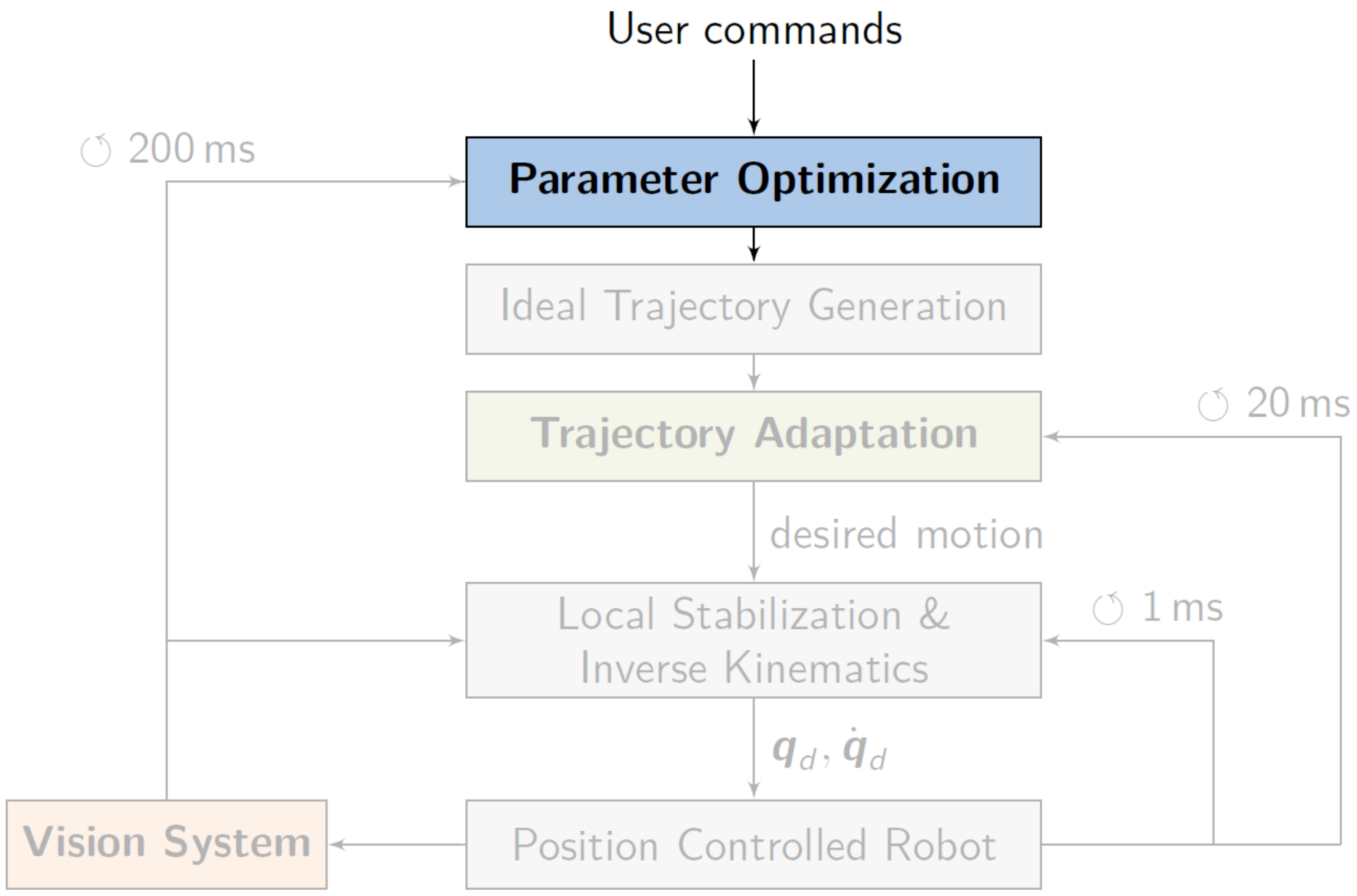

Humanoider Roboter Lola
Lola


Humanoider Roboter Lola
Lola

Real-Time Autonomous Navigation



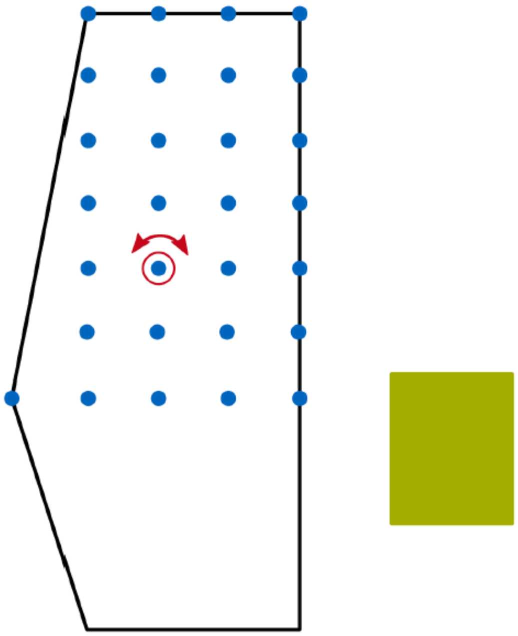
Navigation

Discrete Footholds

Navigation

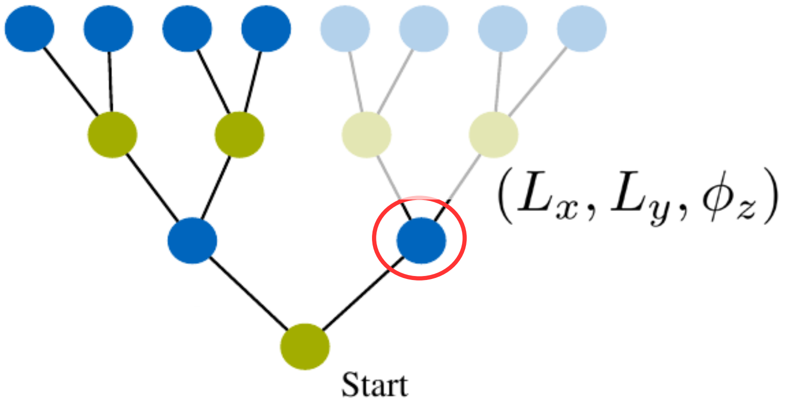
Discrete Footholds

Full-Discretization

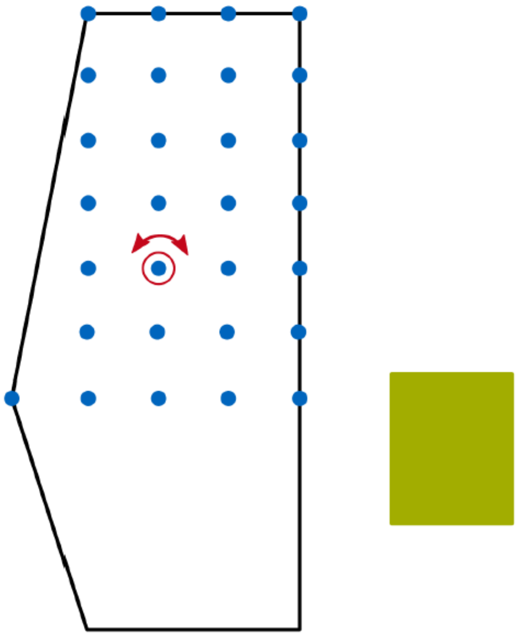


Navigation

Search Tree – A*-Search



Full-Discretization



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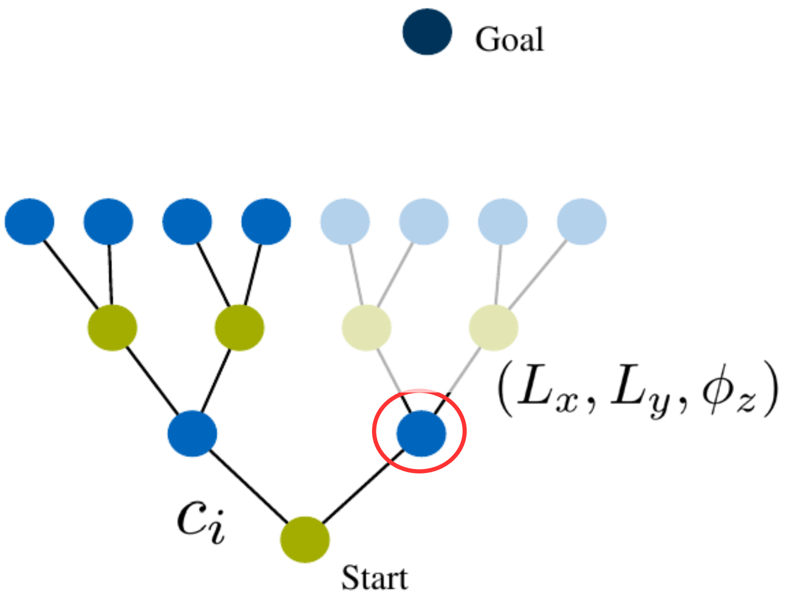
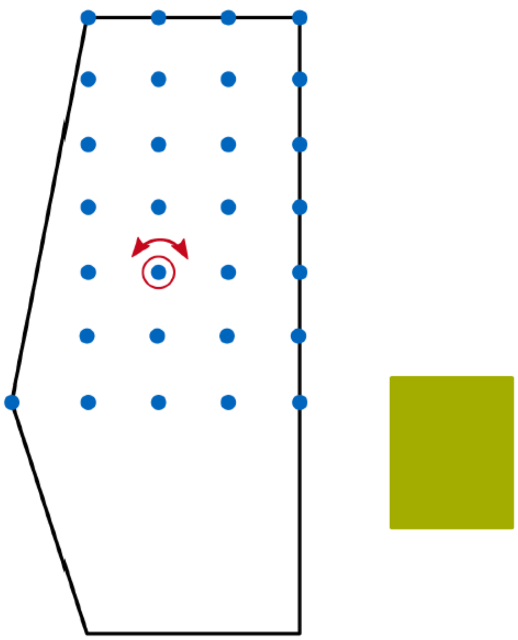
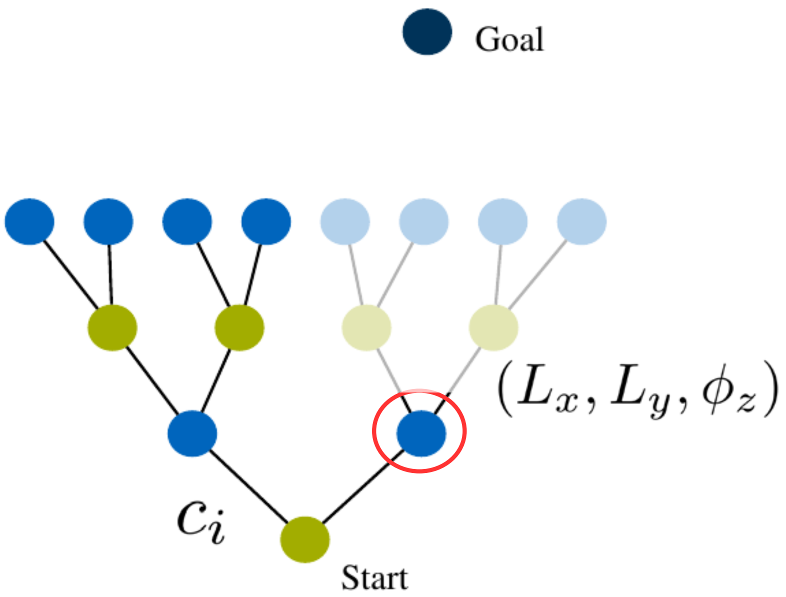


Full-Discretization



Node Analyses

Search Tree – A*-Search

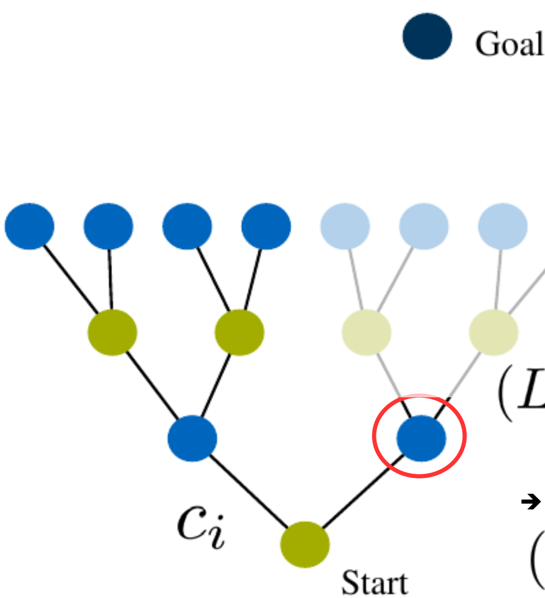


➔ 6D Pose? (L_z, ϕ_y, ϕ_z)

➔ Geometrically Valid?

Node Analyses

Search Tree – A*-Search

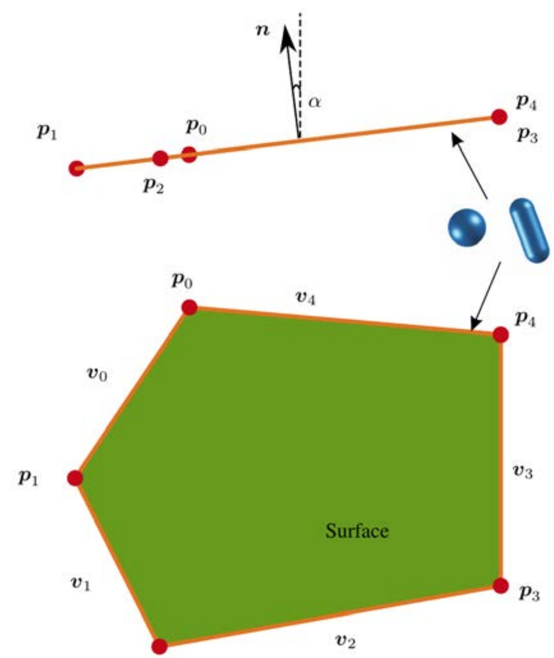


(L_x, L_y, ϕ_z)

➔ 6D Pose?

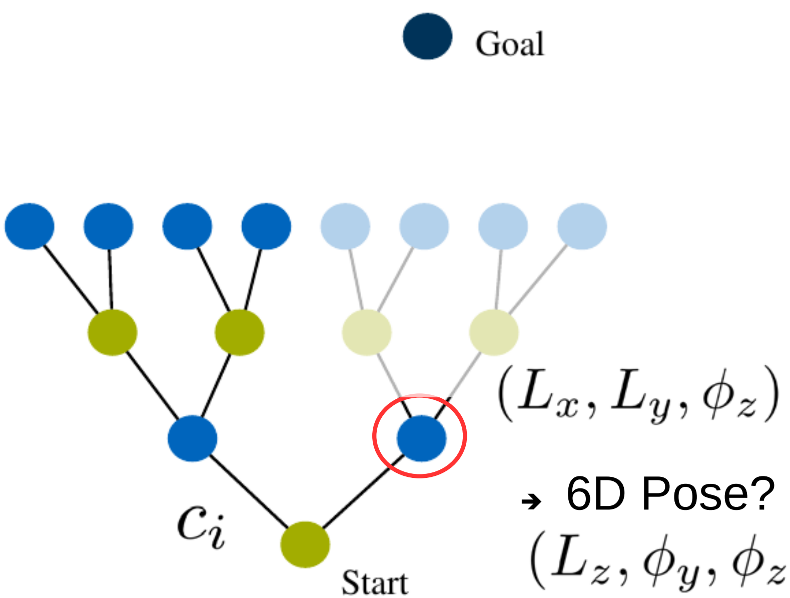
(L_z, ϕ_y, ϕ_z)

6D – Pose : Surface Modelling



Node Analyses

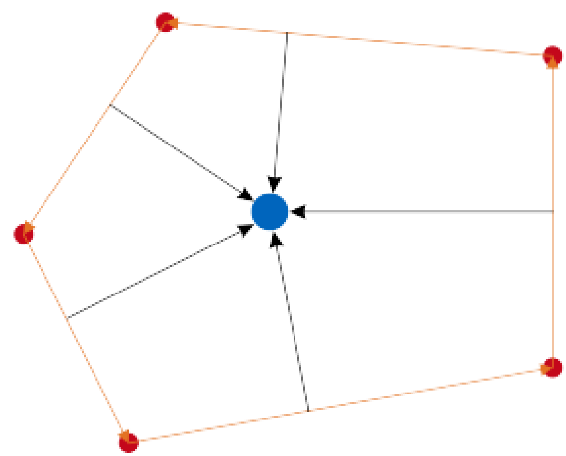
Search Tree – A*-Search



→ 6D Pose?

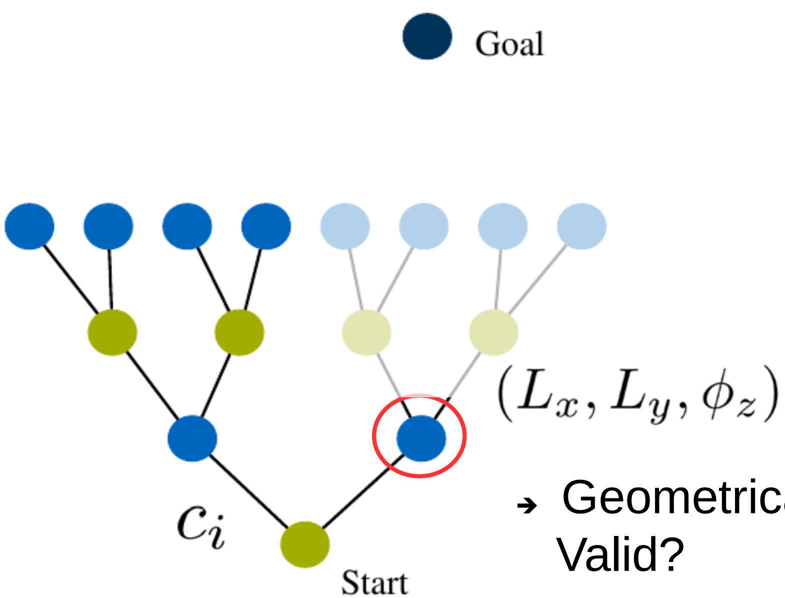
(L_z, ϕ_y, ϕ_z)

6D – Pose : Geometric Position



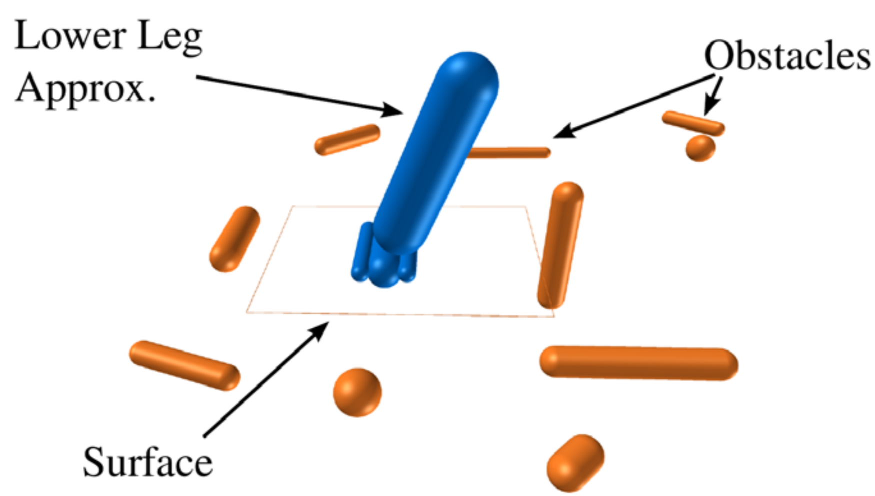
Node Analyses

Search Tree – A*-Search



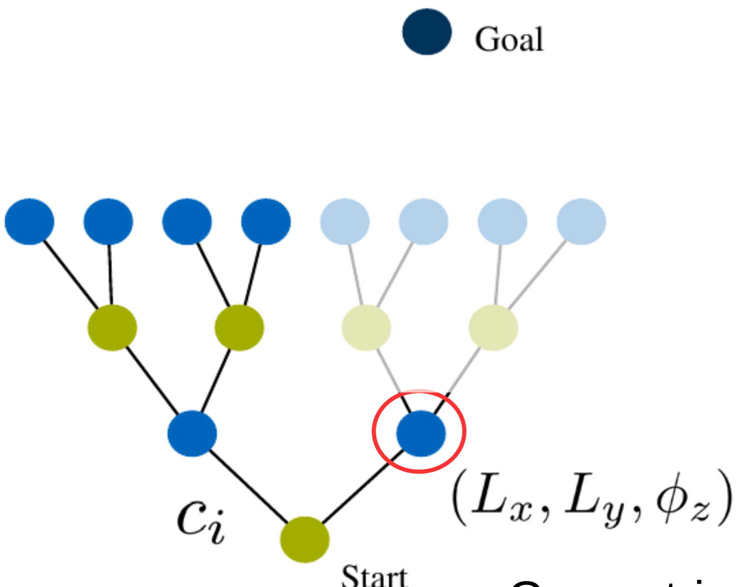
→ Geometrically Valid?

3D - Collision Checking



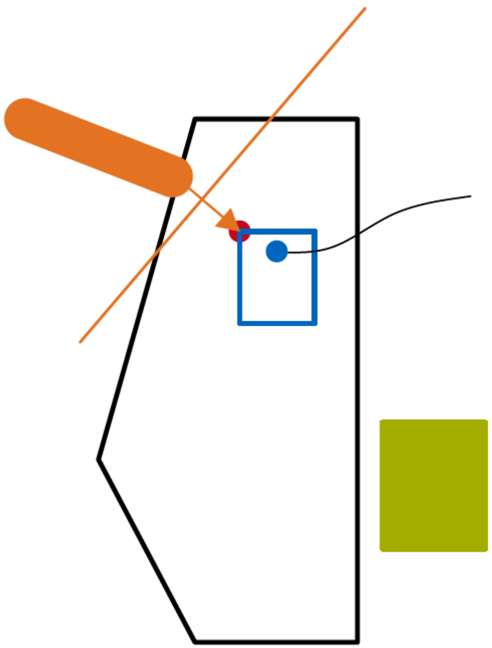
Real Time – Node Optimization

Search Tree – A*-Search

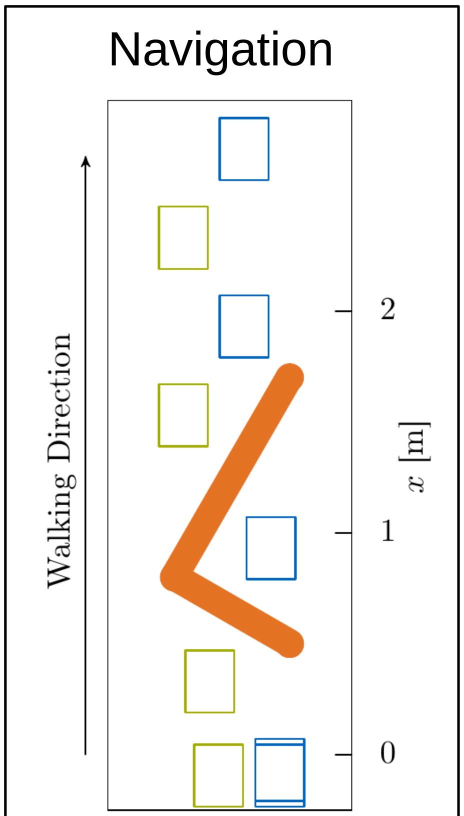


→ Geometrically Valid?

Local Adaption



Motion Generation

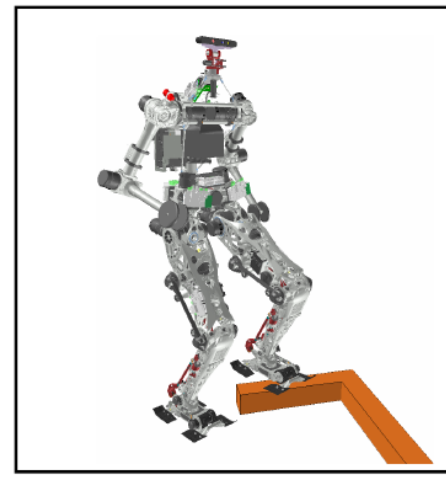


Full-Kinematic Motion?

Stable Walking?

$$T_{Calc} < T_{Step}$$

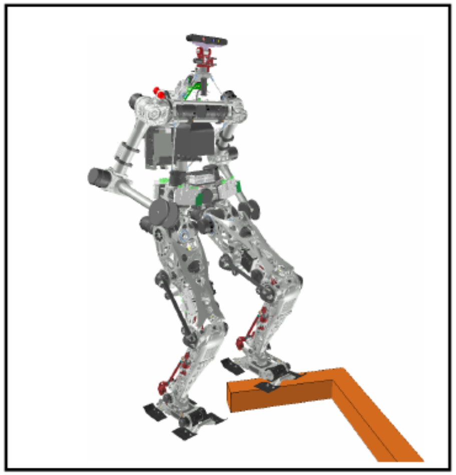
Local Stabilization & Inverse Kinematics



Motion Generation

$$\dot{q} = J^{\#}\dot{w}(t) + Nu(t)$$

Local Stabilization &
Inverse Kinematics

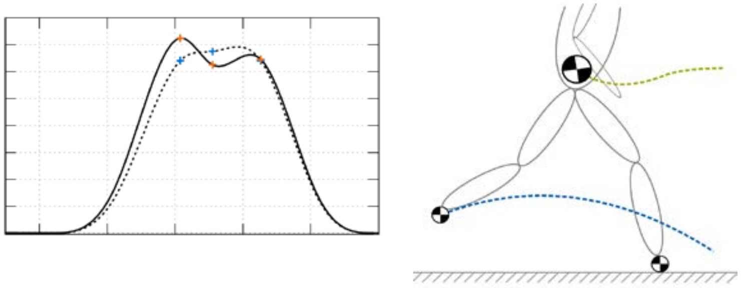


Motion Generation

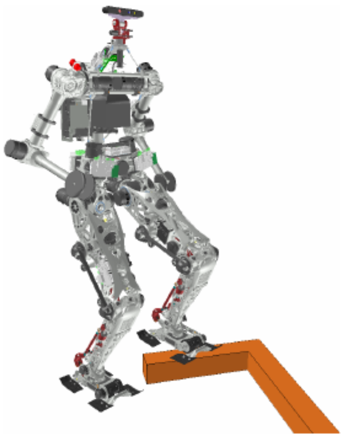
$$\dot{q} = J^{\#}\dot{w}(t) + Nu(t)$$

$$w(t) = w(t, p)$$

Dynamic Constraints



Local Stabilization & Inverse Kinematics



Motion Generation

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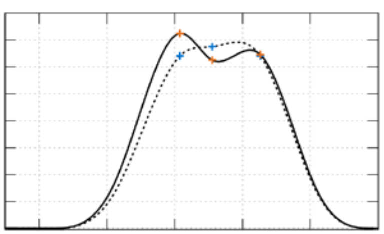
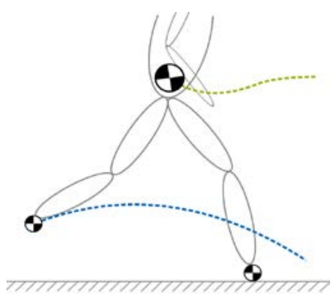
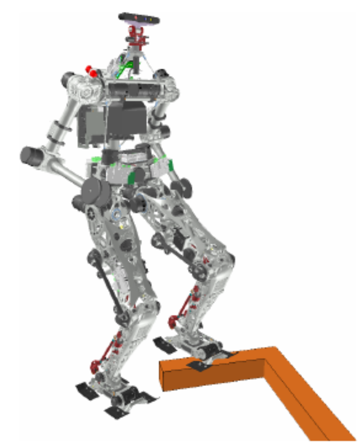




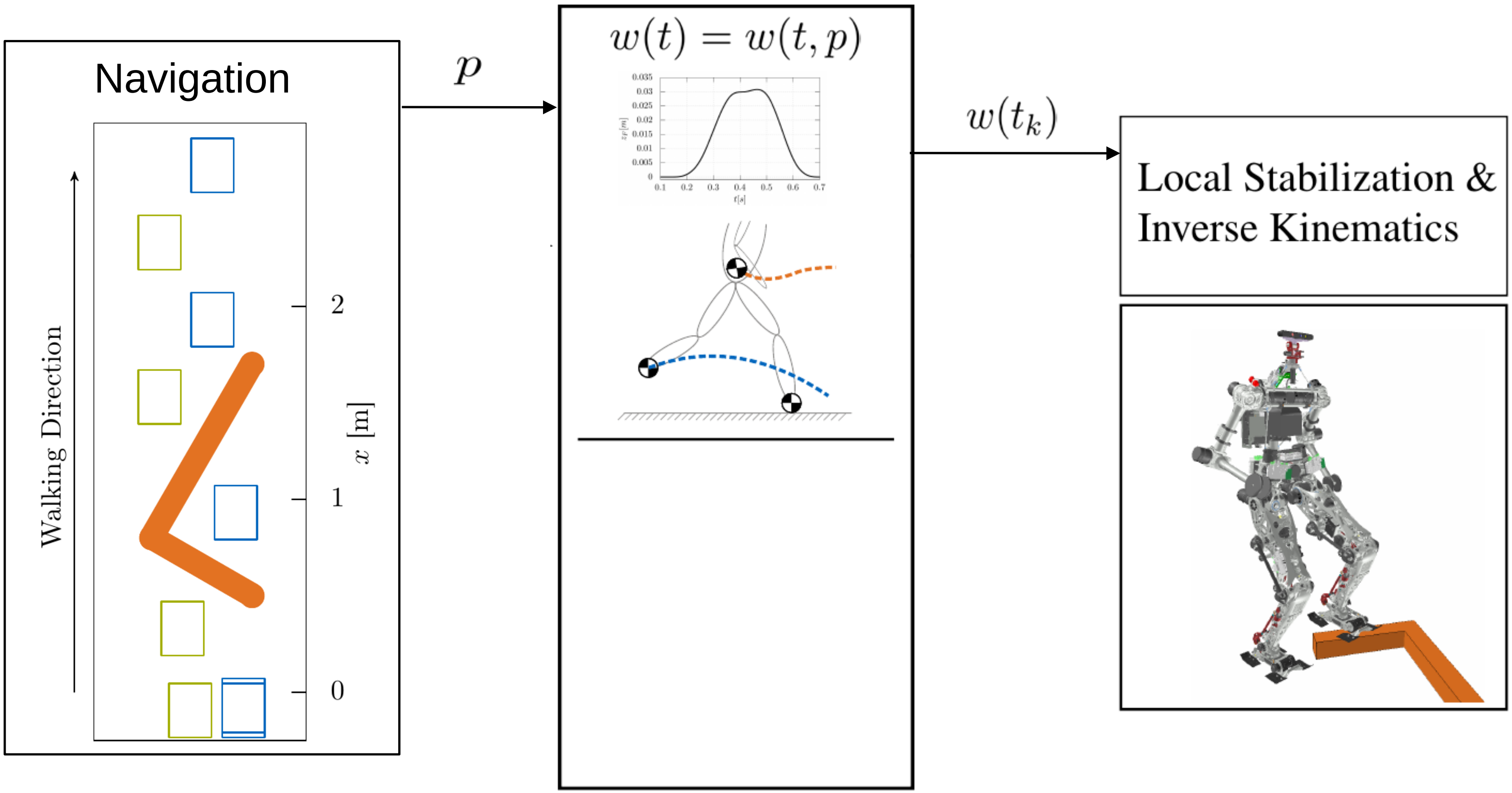
$$u = \alpha \frac{\partial L(q)}{\partial q}$$

Locally

Local Stabilization & Inverse Kinematics



Predictive Kinematic Planning



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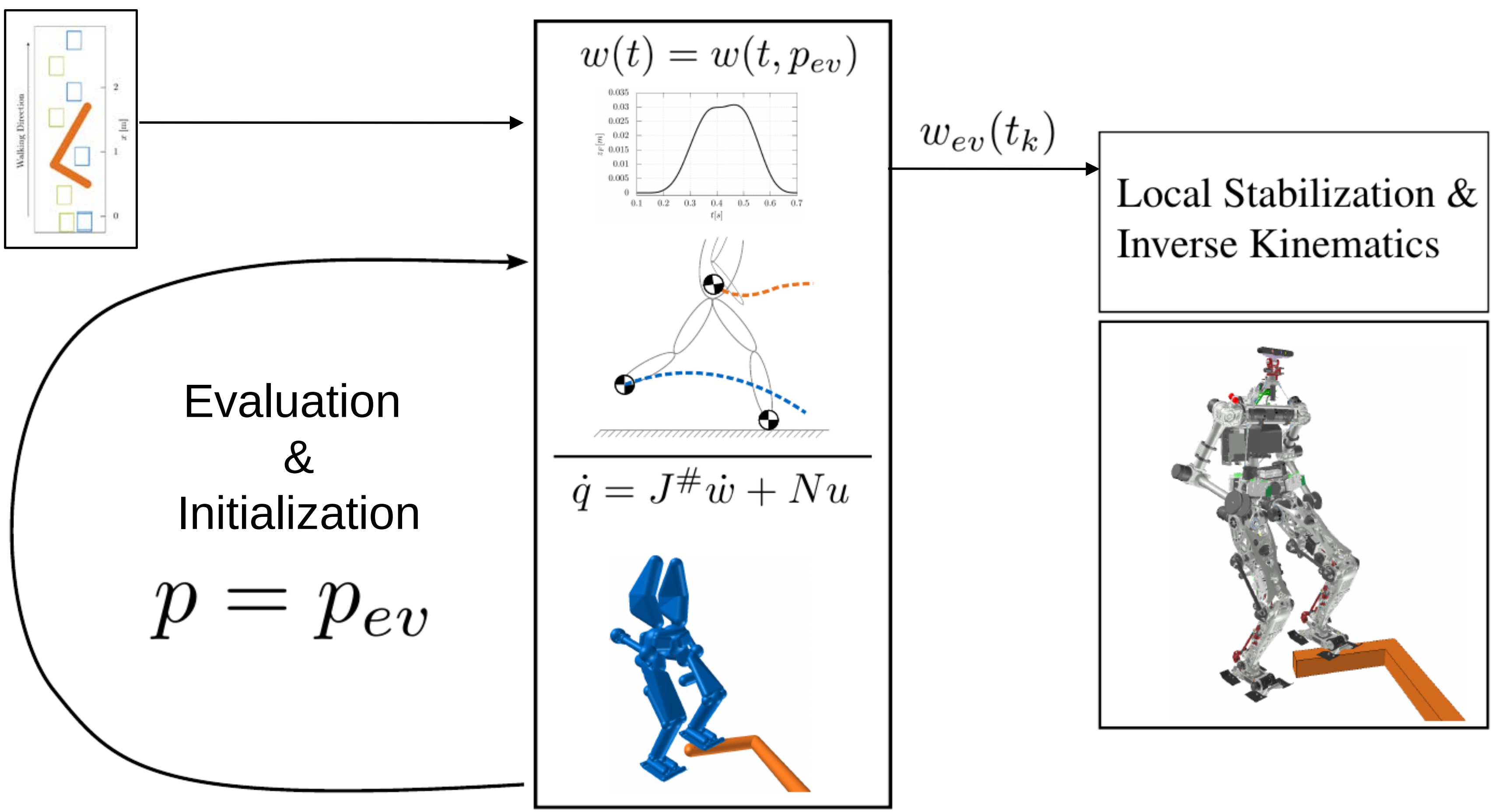

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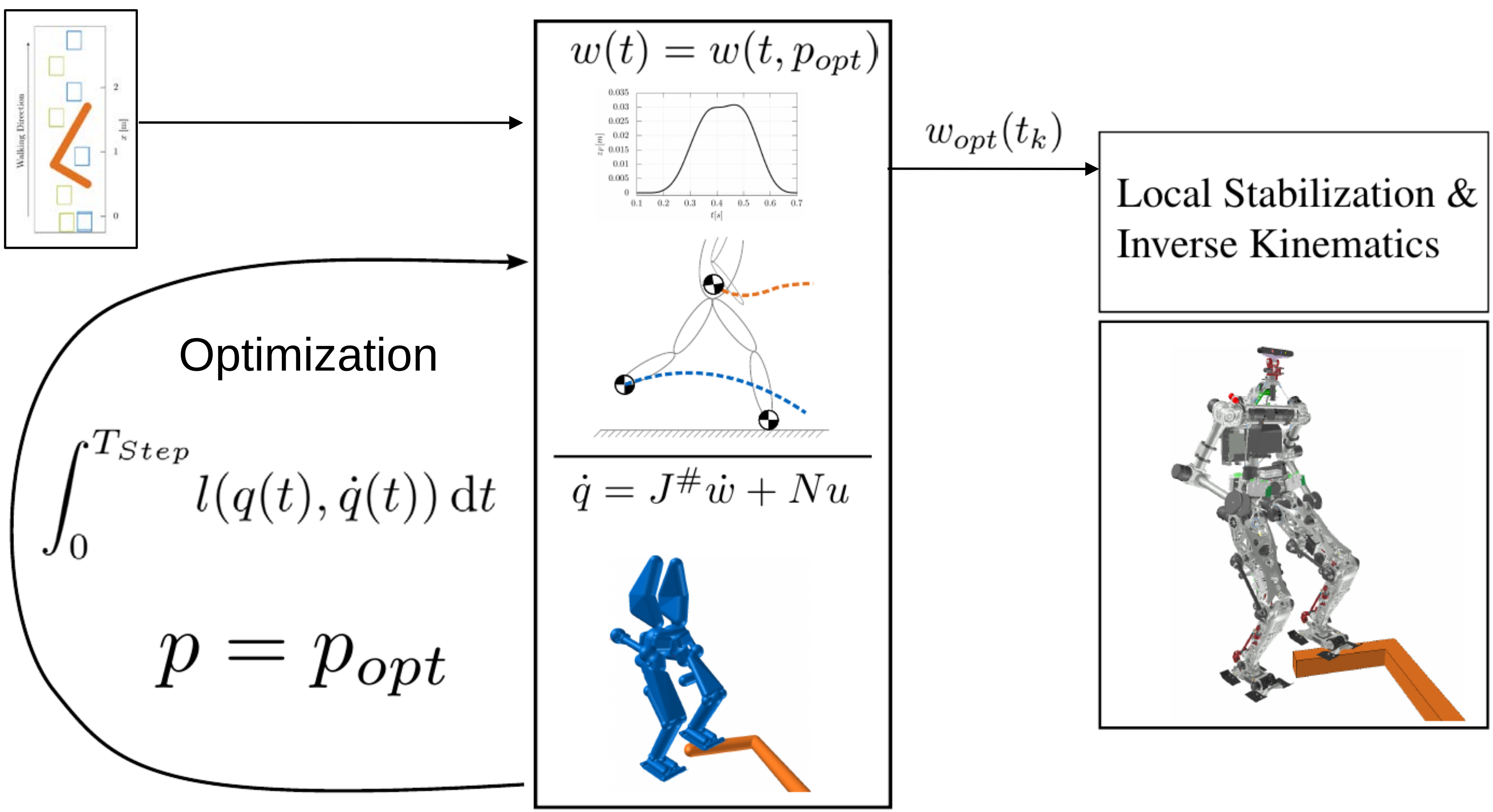

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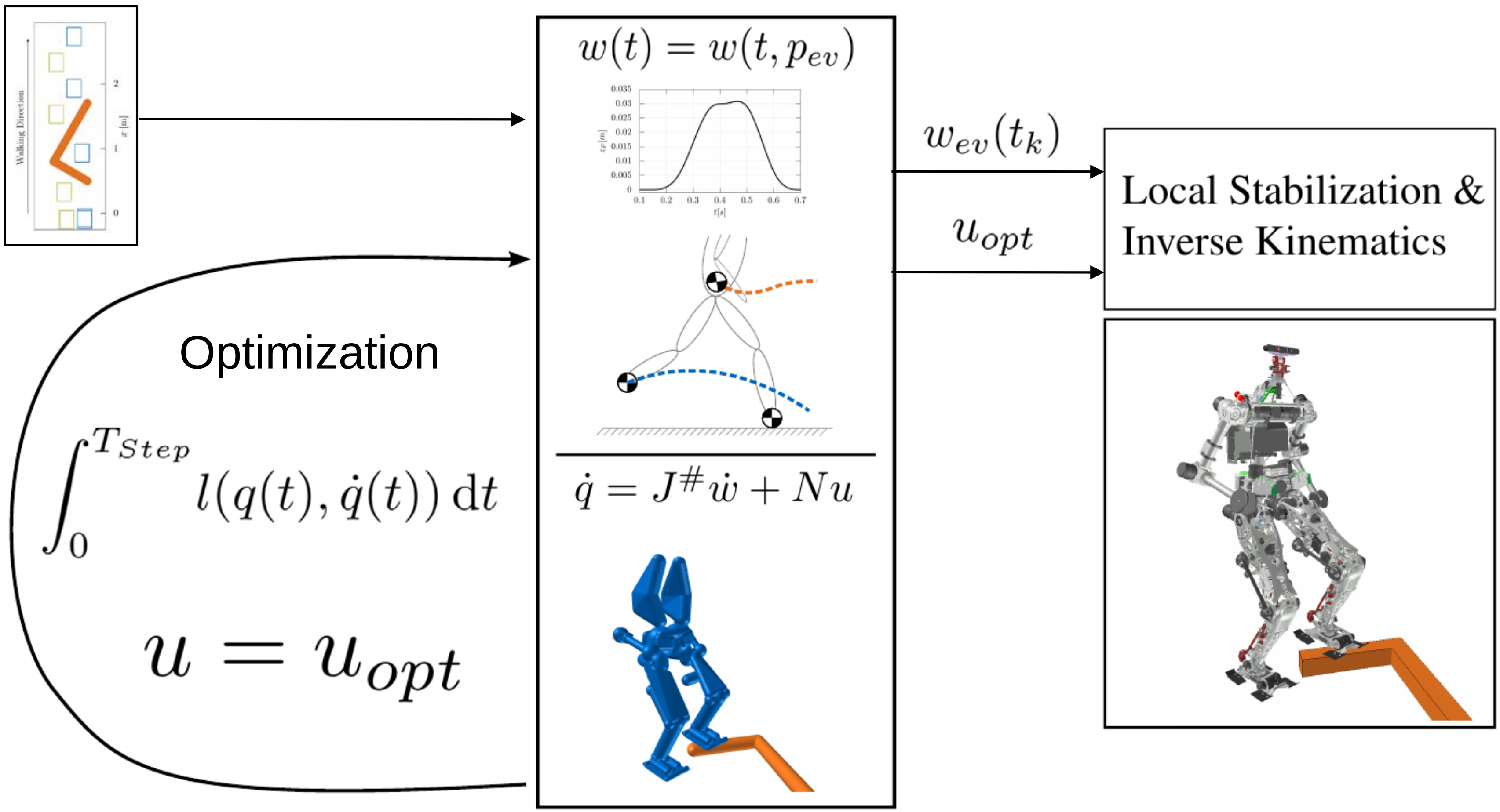

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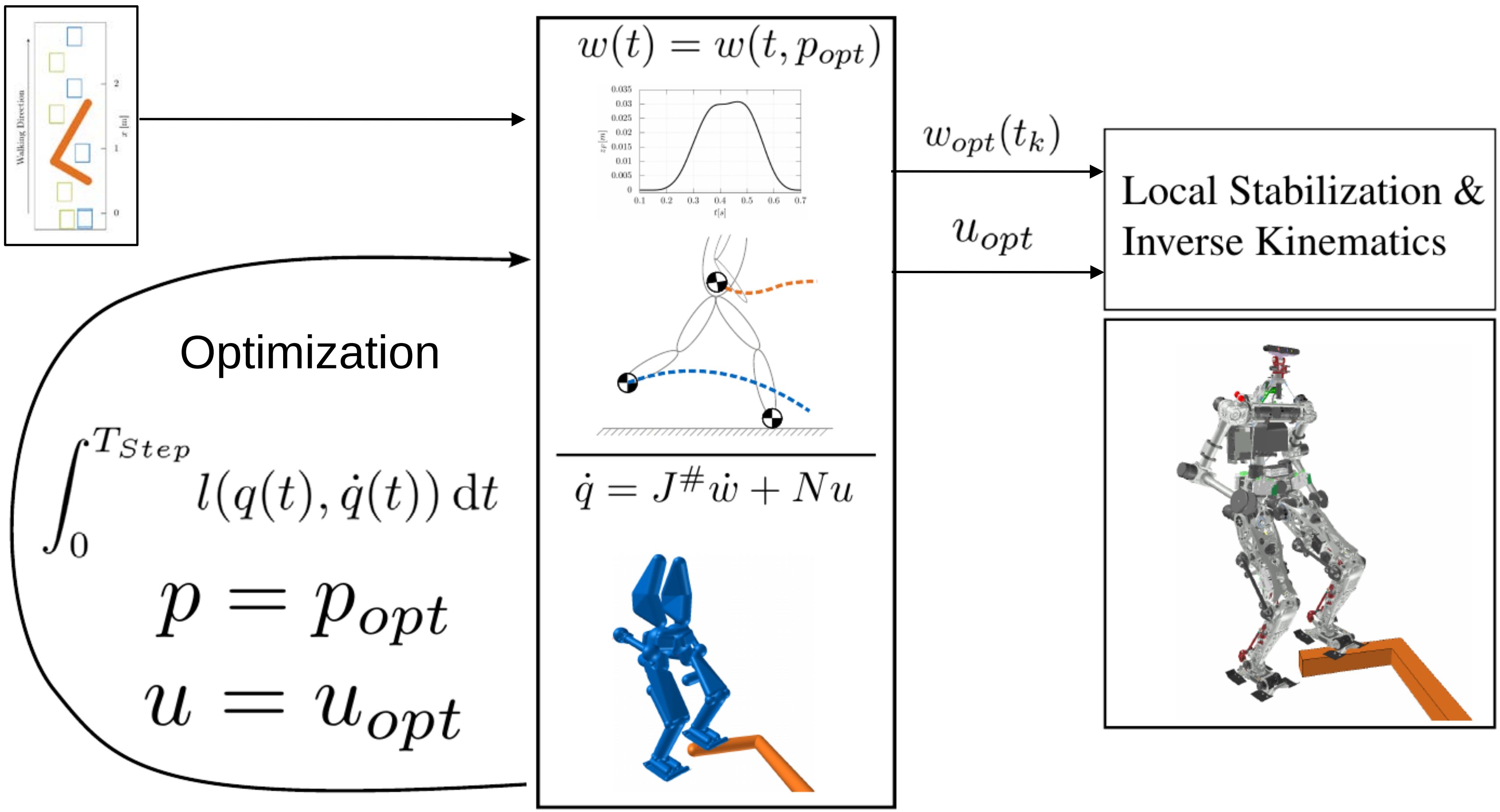
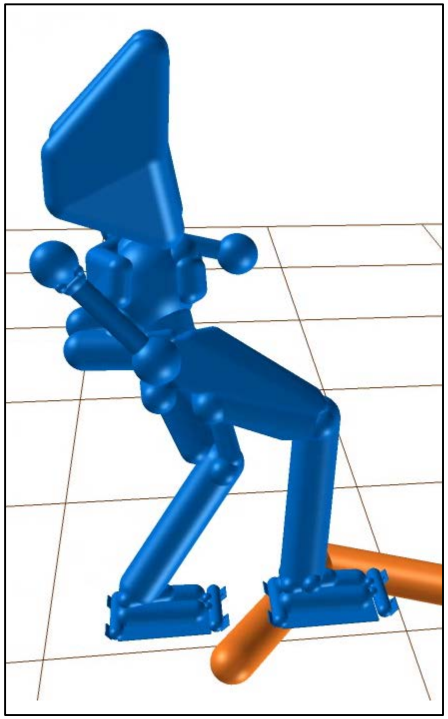
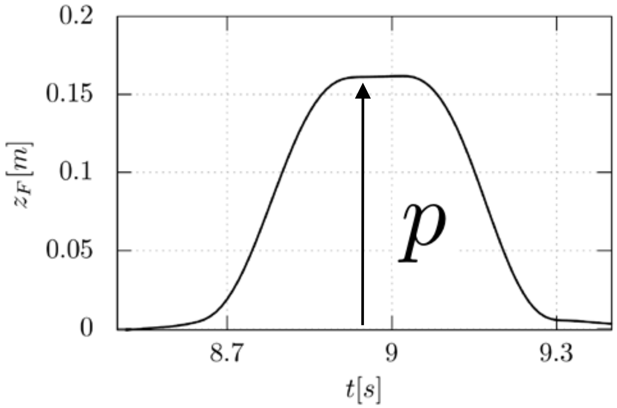
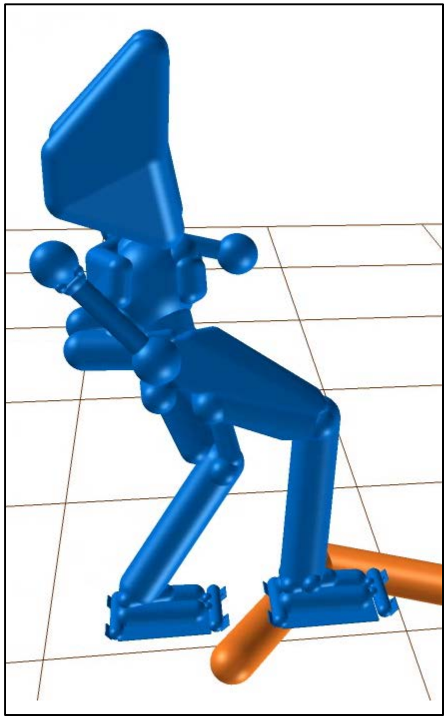


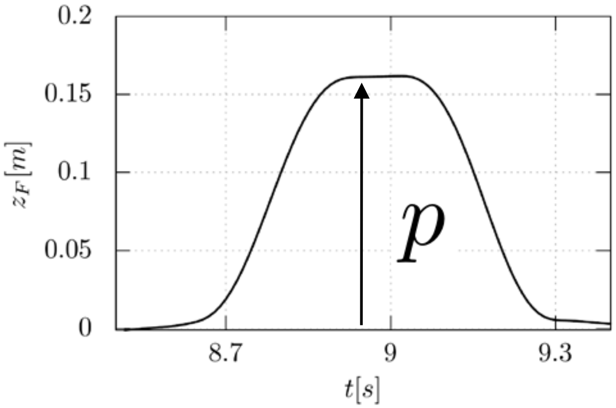
Reactive Adaptation

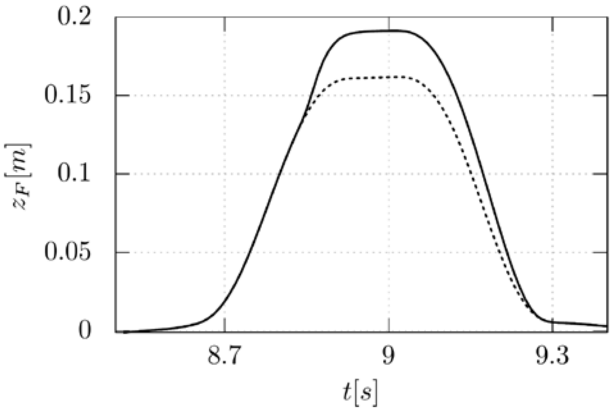




Predictive Kinematic Planning

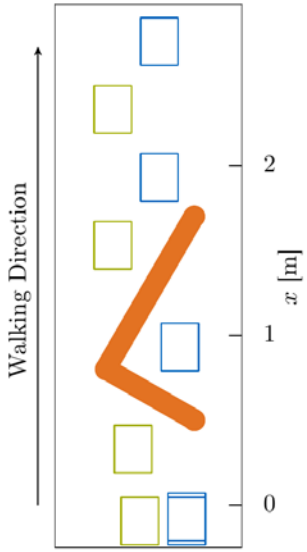




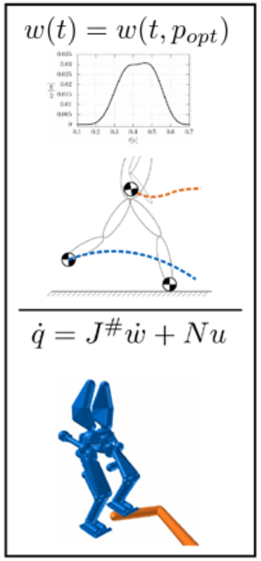


Navigation and Motion Generation

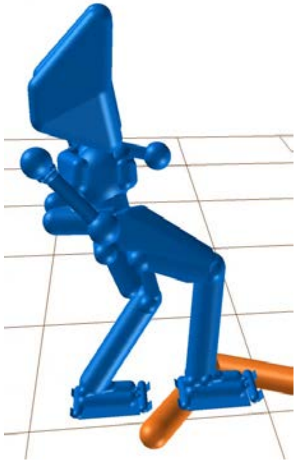
Navigation



Predictive Kinematics



Local Adaptation



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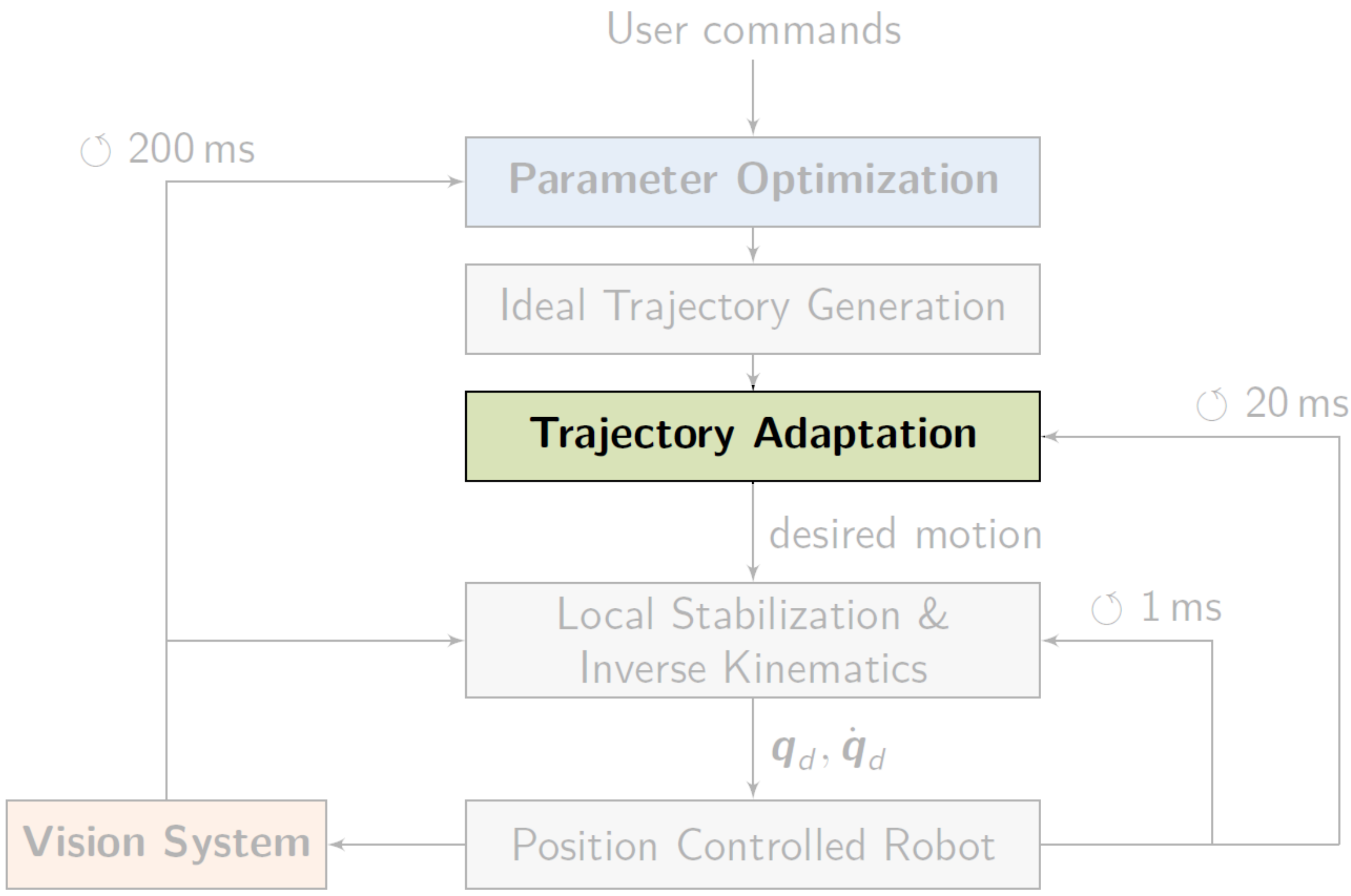
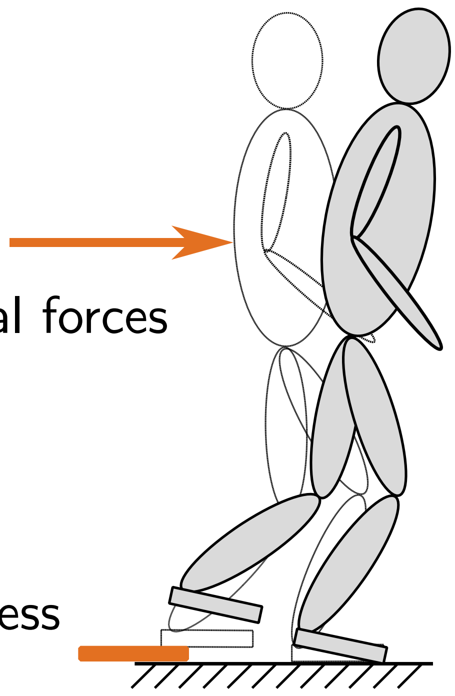


Motivation

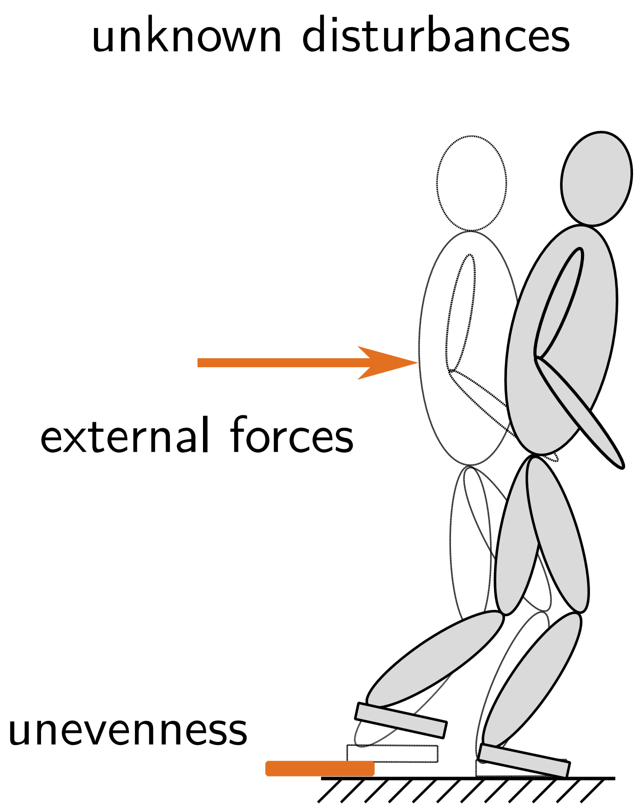
unknown disturbances



external forces

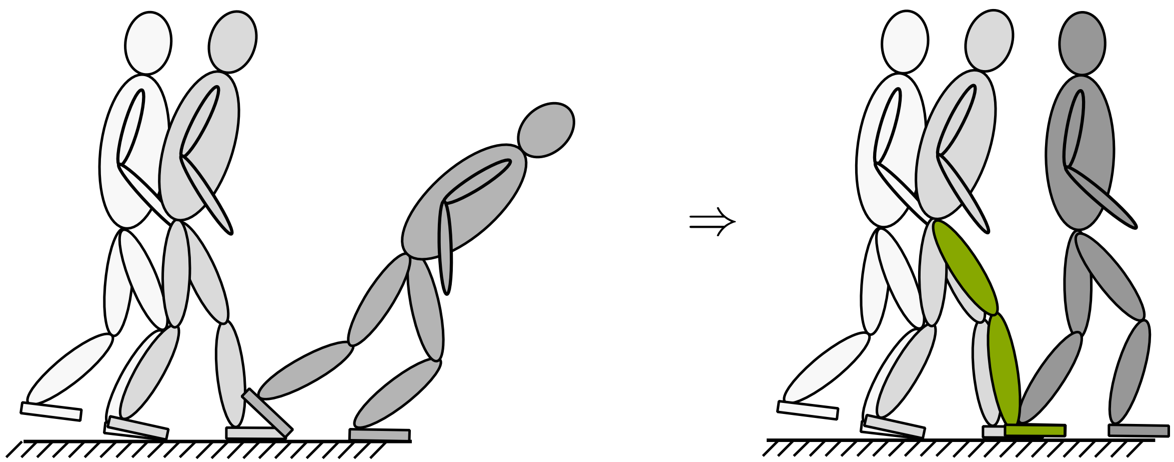
unevenness

Motivation



- current state?
- divergence?
- adapt **future** motion?

Solution?



Solution

- current state? $\longrightarrow$ state estimator
- divergence? $\longrightarrow$ prediction model
- adapt **future** motion? $\longrightarrow$ trajectory optimization

Solution

- current state? $\rightarrow$ state estimator
- divergence? $\rightarrow$ prediction model
- adapt **future** motion? $\rightarrow$ trajectory optimization

---

- input?
  - inertial measurements (IMU)
  - ideal planned motion

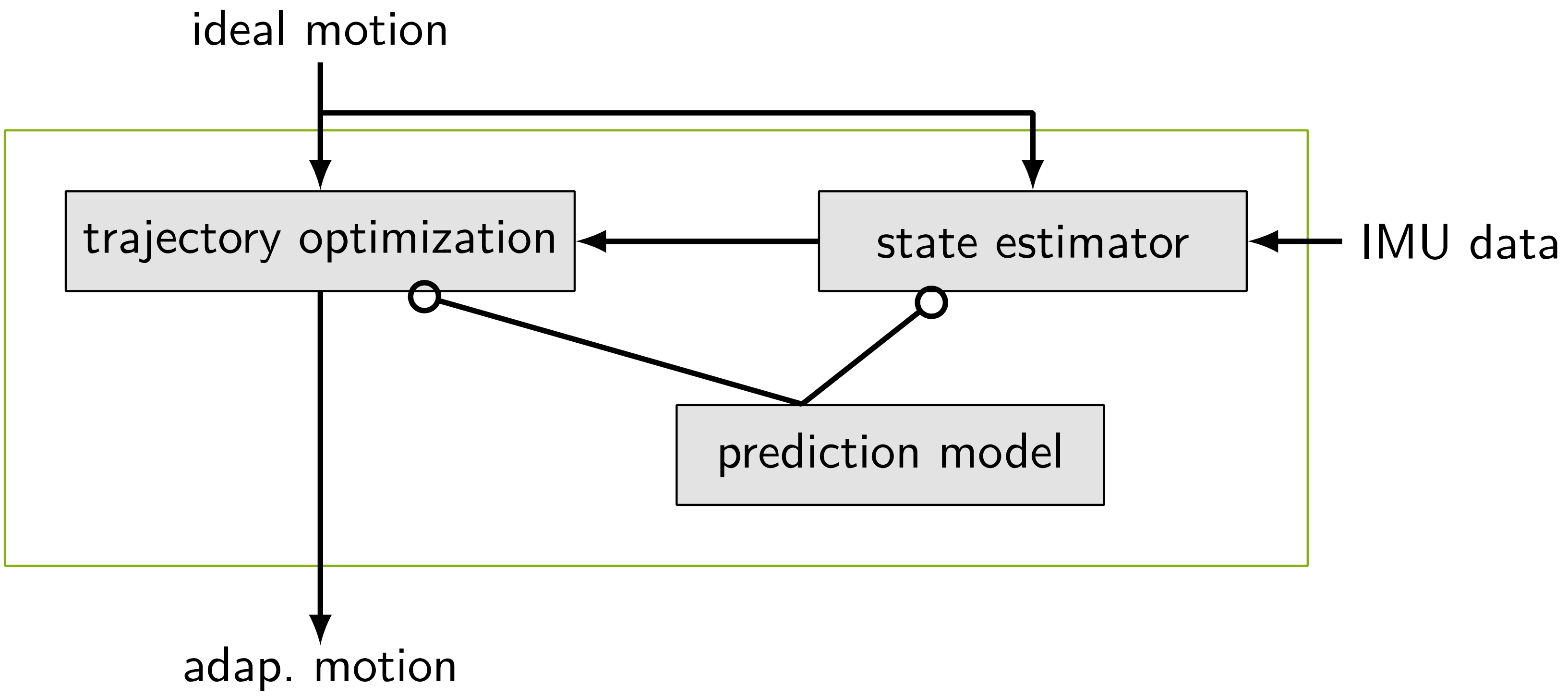
Solution

- current state? $\rightarrow$ state estimator
- divergence? $\rightarrow$ prediction model
- adapt **future** motion? $\rightarrow$ trajectory optimization

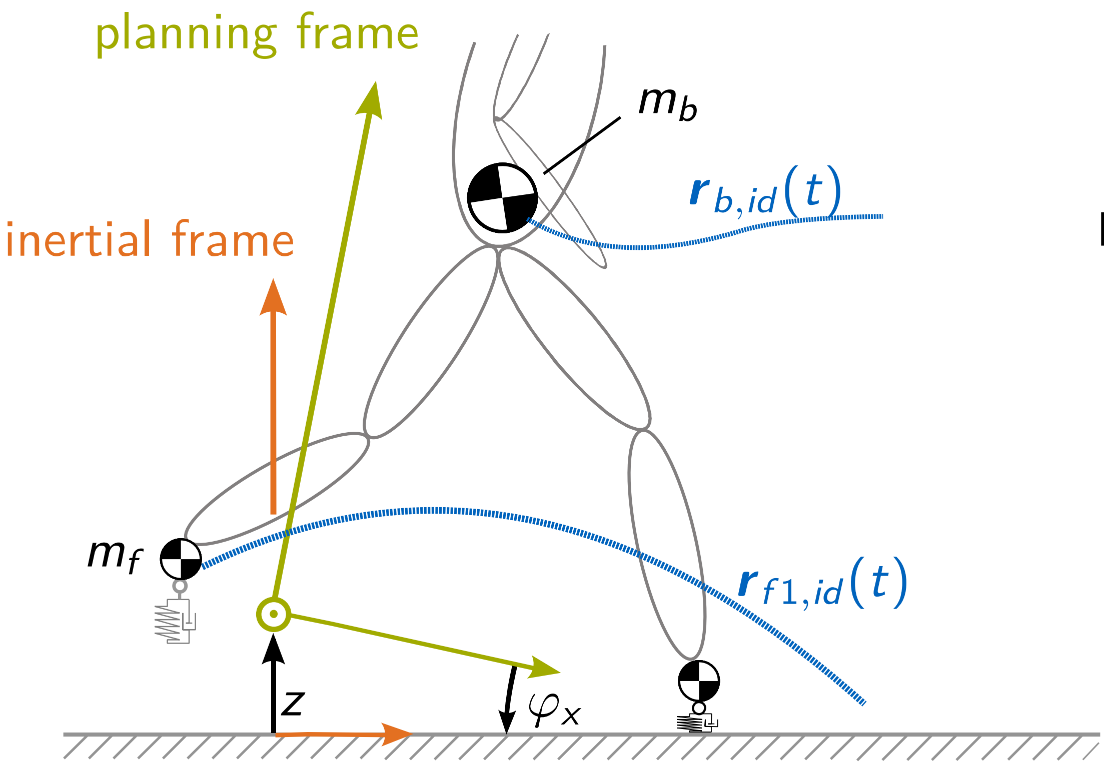
---

- input?
  - inertial measurements (IMU)
  - ideal planned motion
- output?
  - modified foot trajectories
  - modified center of gravity trajectories

Trajectory Adaptation



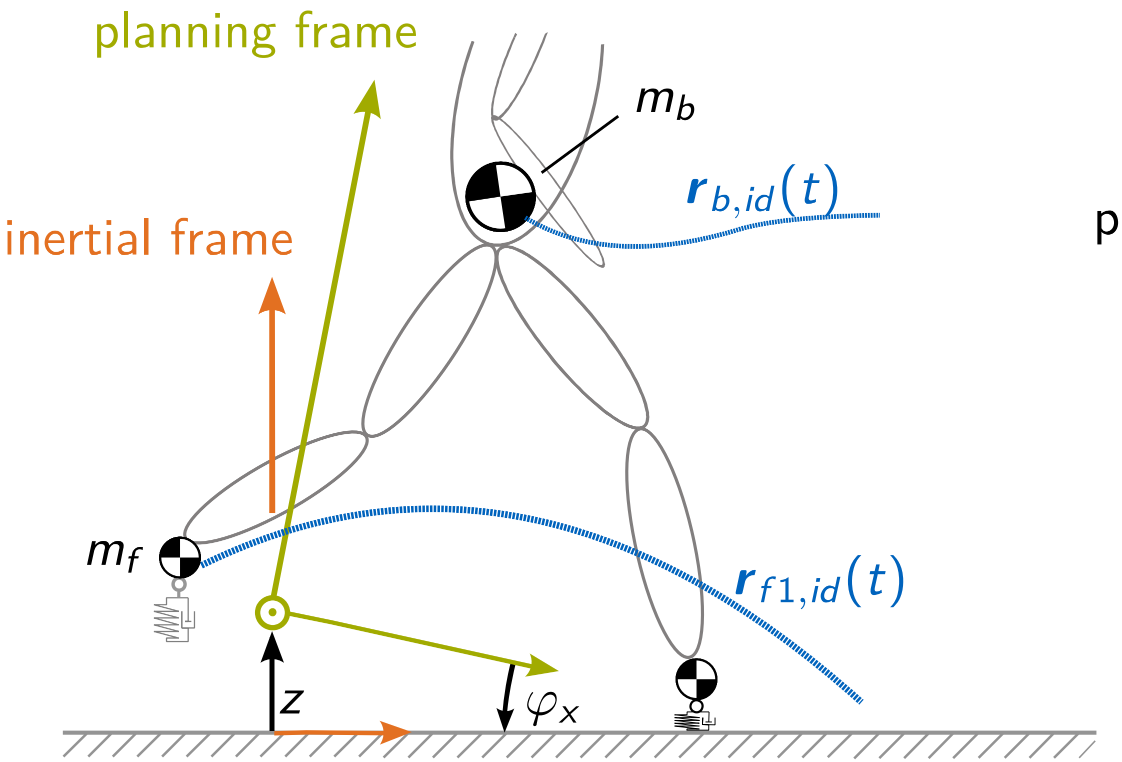
Dynamic Prediction Model



properties:

- planar
- 3 point masses

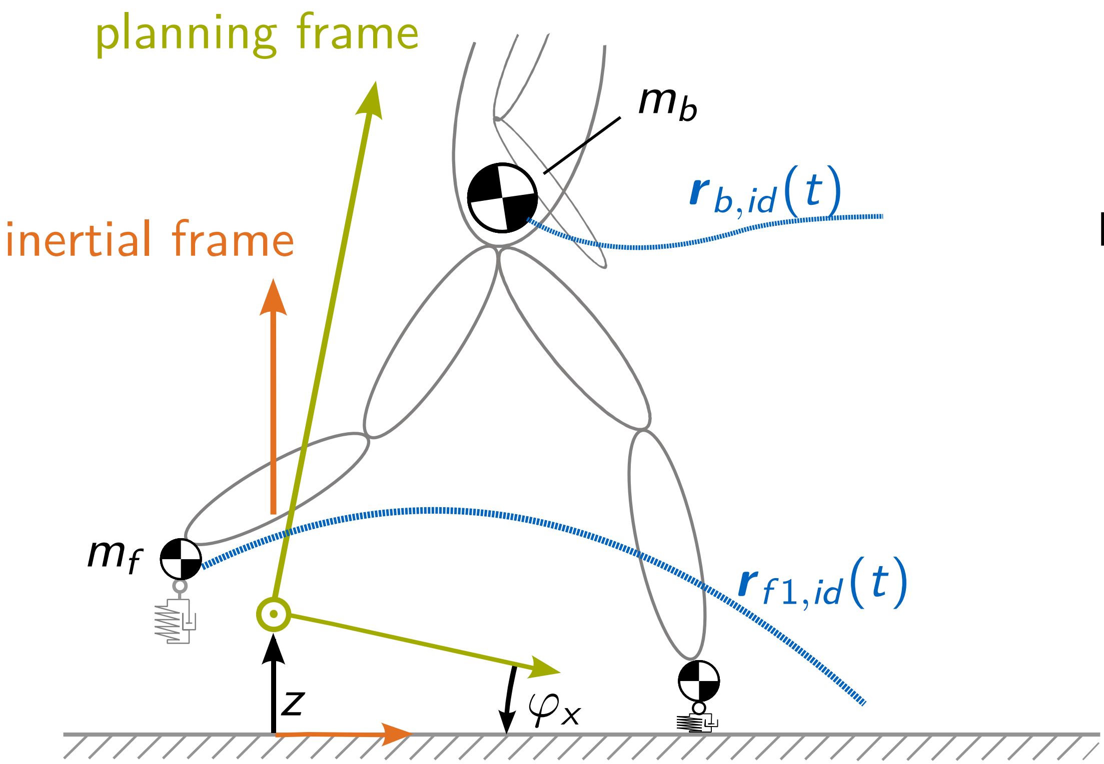
Dynamic Prediction Model



properties:

- planar
- 3 point masses
- 2 unilateral contacts
- 2 passive dofs

Dynamic Prediction Model



properties:

- planar
- 3 point masses
- 2 unilateral contacts
- 2 passive dofs
- local contact force control

Dynamic Prediction Model

- nonlinear dynamics

$$\boldsymbol{M}(\boldsymbol{q}, t)\ddot{\boldsymbol{q}} + \boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}}, t) = \boldsymbol{\lambda}(\boldsymbol{q}, \dot{\boldsymbol{q}}, t) + \boldsymbol{T}_s(\boldsymbol{q}, \dot{\boldsymbol{q}})$$

Dynamic Prediction Model

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- switching contact states

$$\boldsymbol{\lambda} = \sum_{i \in N_C} \left(\frac{\partial \boldsymbol{r}_{Fi}}{\partial \boldsymbol{q}} \right)^T \boldsymbol{F}_i$$

Dynamic Prediction Model

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Dynamic Prediction Model

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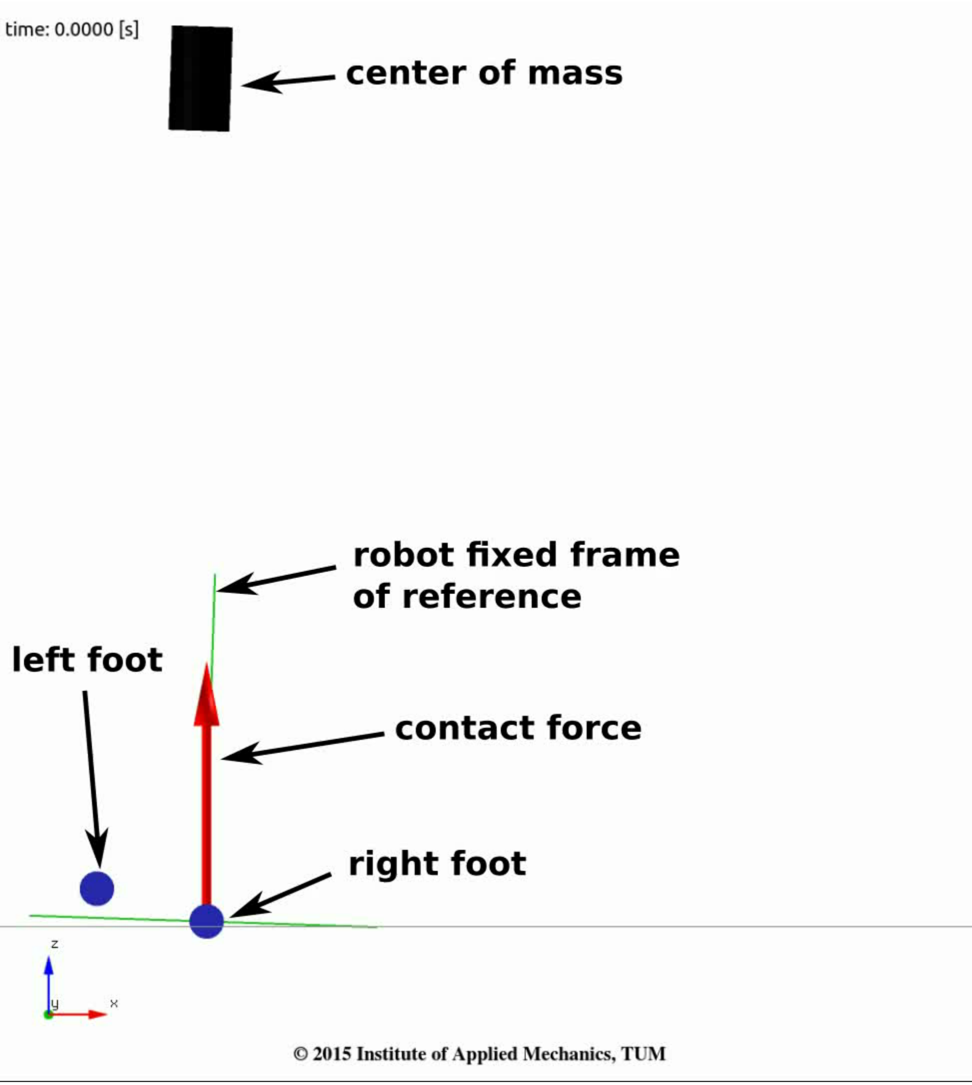
- local force control

$$\boldsymbol{T}_s = [0, \mathrm{sat}(-K_p \Delta\varphi_x - K_d \Delta\dot{\varphi}_x)]^T$$

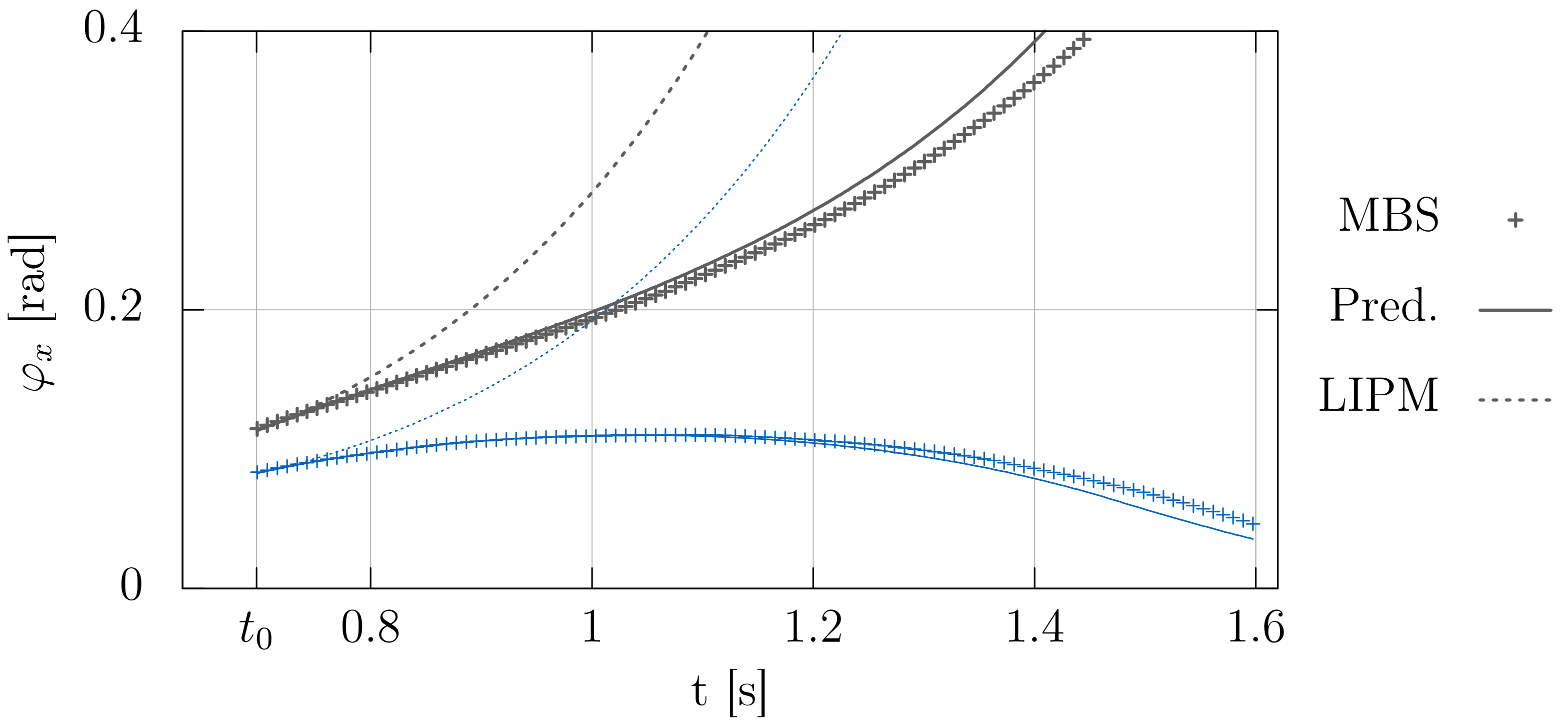
- computation time (Horizon $T = 1\,\mathrm{s}$, forward Euler $\triangle t = 3\,\mathrm{ms}$)
  $\rightarrow \quad \approx 50\,\mu\mathrm{s}$

Prediction Result



Verification – Simulation

proposed model vs. pendulum:

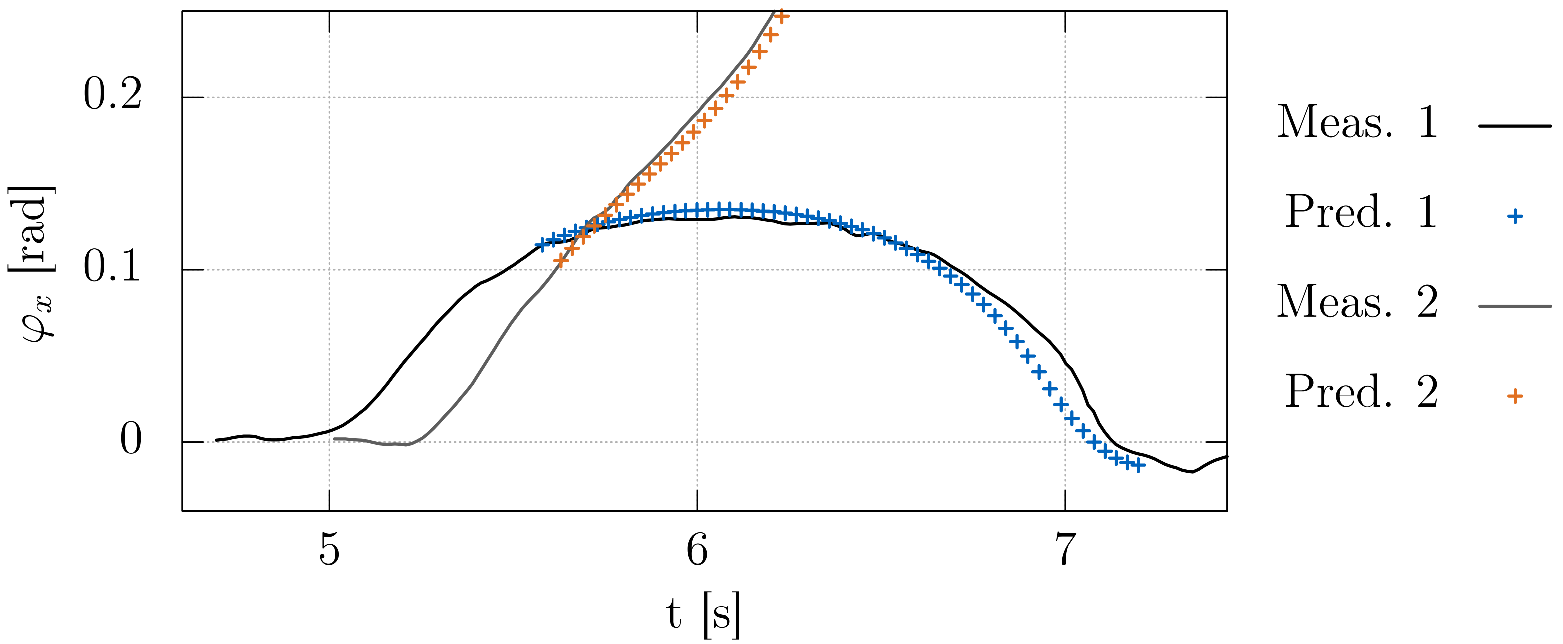


Verification – Measurements

- absolute inclination φ
- measurement vs. prediction model

Verification – Measurements

- absolute inclination φ
- measurement vs. prediction model

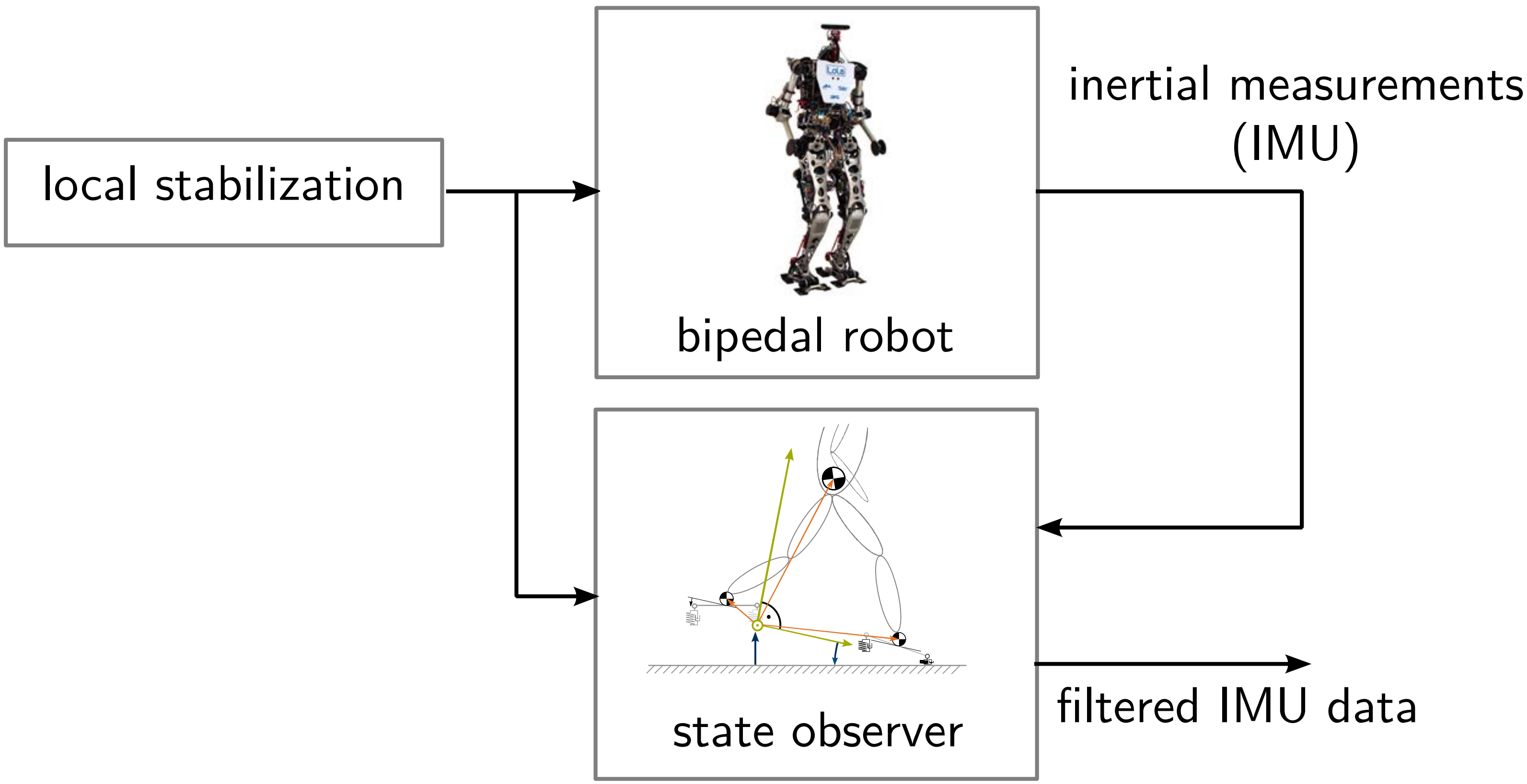


State Estimation - Extended Kalman Filter

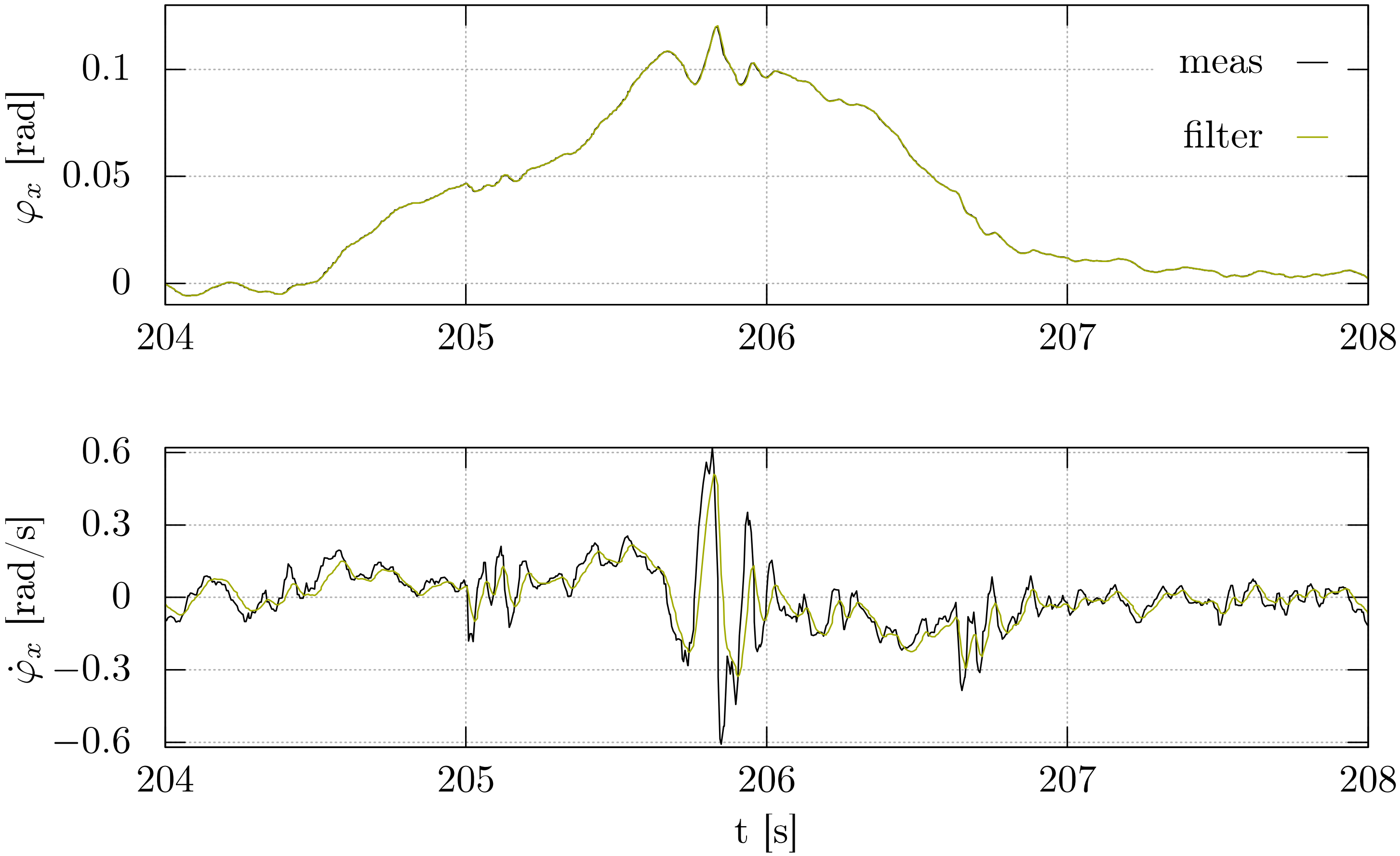
estimate for inertial/absolute pose

State Estimation - Extended Kalman Filter

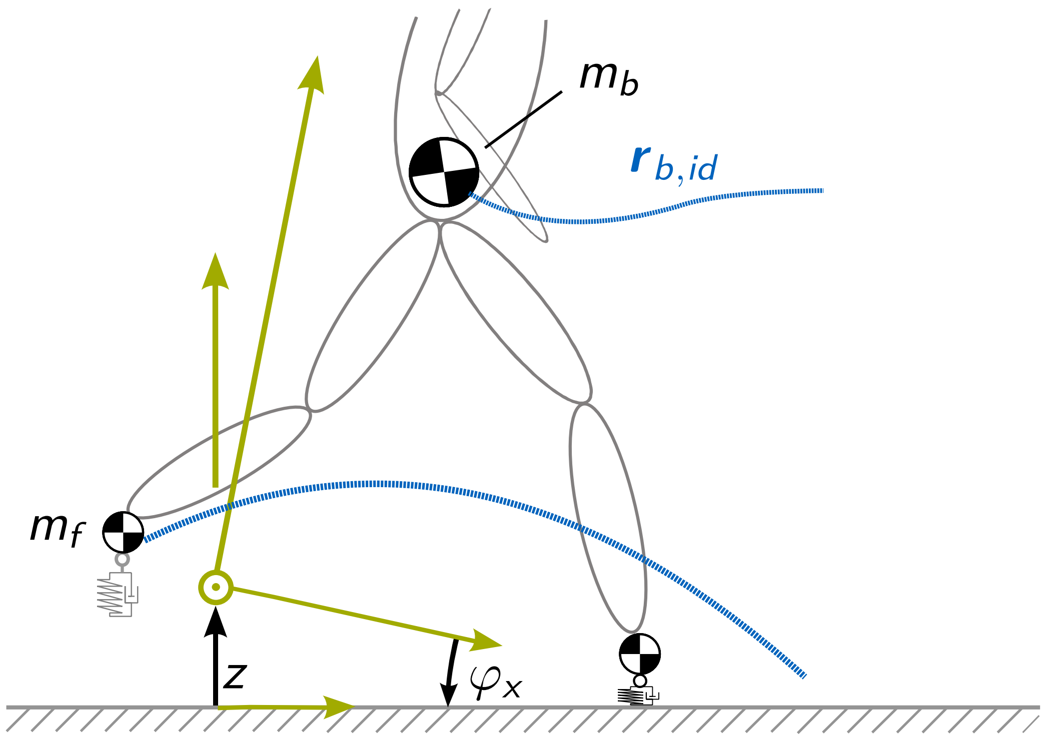
estimate for inertial/absolute pose



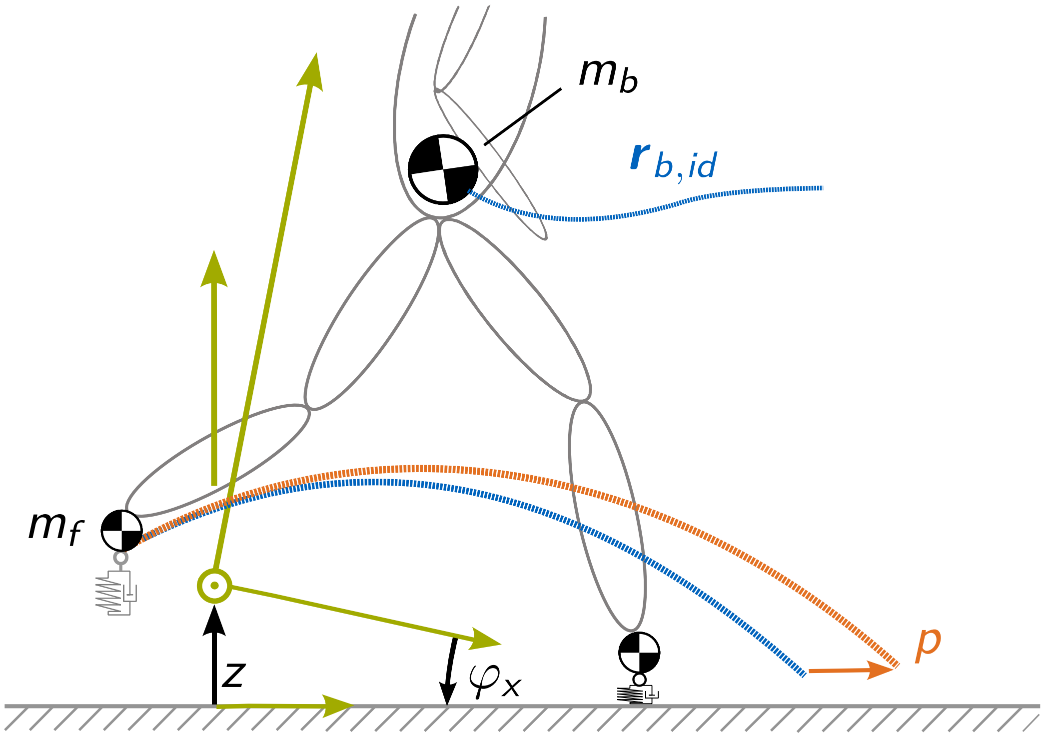
State Estimator - Kalman Filter



Model with Modifications



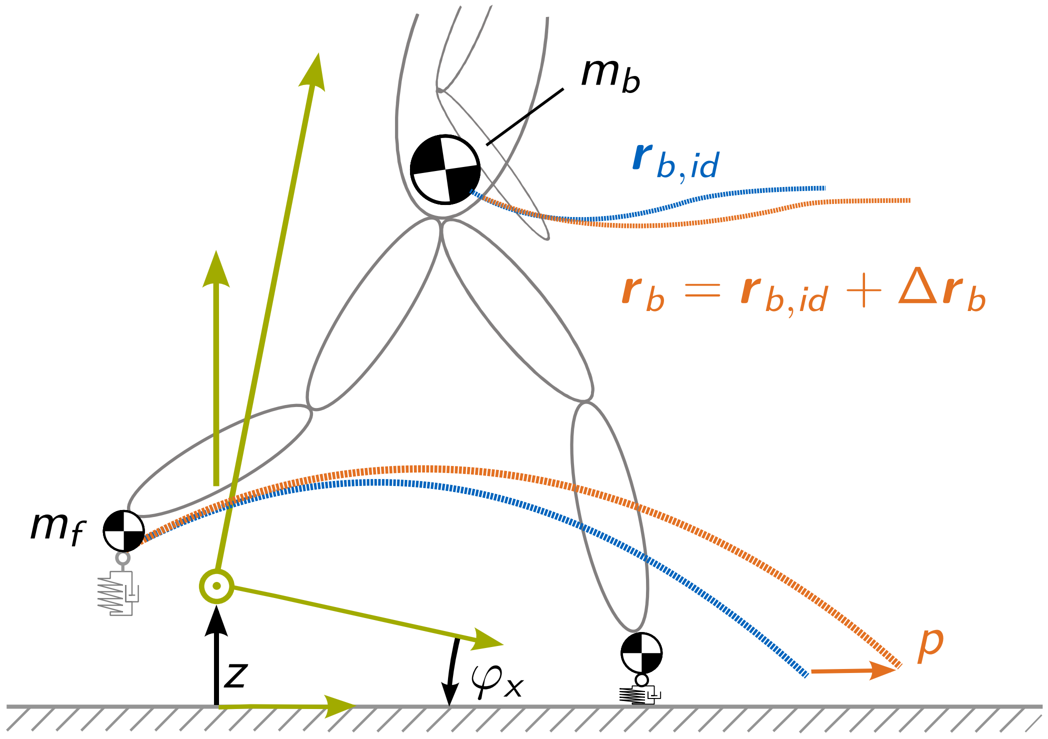
Model with Modifications



modifications:

- final swing foot position p

Model with Modifications



modifications:

- final swing foot position p
- CoG trajectory $\Delta \boldsymbol{r}_b(t)$

Model with Modifications

- swing foot modification (5th order polynomial):

$$\boldsymbol{r}_{f1} = \boldsymbol{r}_{f1,id} + \Delta\boldsymbol{r}_{f1}(p)$$

Model with Modifications

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$$\boldsymbol{r}_{f1} = \boldsymbol{r}_{f1,id} + \Delta \boldsymbol{r}_{f1}(p)$$

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$$\boldsymbol{r}_{b} = \boldsymbol{r}_{b,id} + \Delta \boldsymbol{r}_{b} = \begin{bmatrix} x_{b,id} \\ 0 \\ z_{b,id} \end{bmatrix} + \begin{bmatrix} \Delta x_{b} \\ 0 \\ 0 \end{bmatrix}, \qquad u = \Delta \ddot{x}_{b}$$

Model with Modifications

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- EoM with modifications

$$\dot{\boldsymbol{x}} = \frac{\mathrm{d}}{\mathrm{d}t} \begin{bmatrix} \boldsymbol{q} \\ \dot{\boldsymbol{q}} \\ \Delta x_b \\ \Delta\dot{x}_b \end{bmatrix} = \begin{bmatrix} \dot{\boldsymbol{q}} \\ \boldsymbol{M}^{-1}[\lambda(p) + \boldsymbol{T}_s - \boldsymbol{h}] \\ \Delta\dot{x}_b \\ u \end{bmatrix} = \boldsymbol{f}(\boldsymbol{x}, t, p, u)\,.$$

Optimization Problem

$$
\begin{aligned}
\min_{p, u(t)} J = \min_{p, u(t)} & \left[s(\boldsymbol{x}(t_f), p) + \int\limits_{t_0}^{t_f} h(\boldsymbol{x}, p, u, t) \mathrm{d}t \right], \\
\text{s.t.} \quad & \dot{\boldsymbol{x}}(t) = \boldsymbol{f}(\boldsymbol{x}, p, u(t), t), \quad \text{(prediction model)} \\
& \boldsymbol{x}(t_0) = \boldsymbol{x}_0, \quad \text{(estimated state)} \\
& u(t) \in \mathcal{U}, \\
& p \in \mathcal{P}.
\end{aligned}
$$

Optimization Problem

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- real-time solution with conjugate gradient method

Optimization Problem

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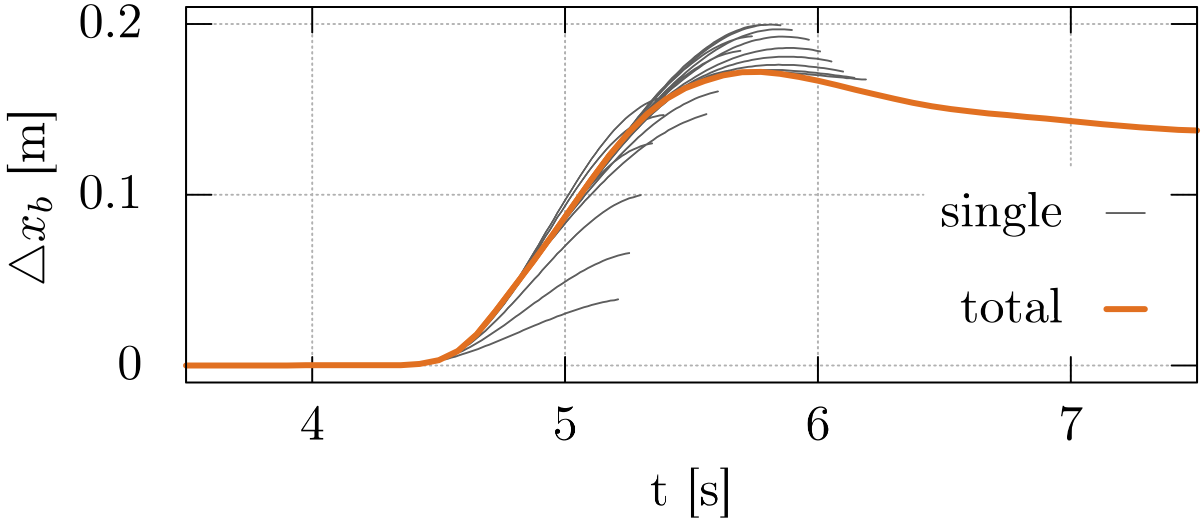
- real-time solution with conjugate gradient method
- receeding horizon with 50 Hz
- 3 iterations take max. 3.5 ms

Results

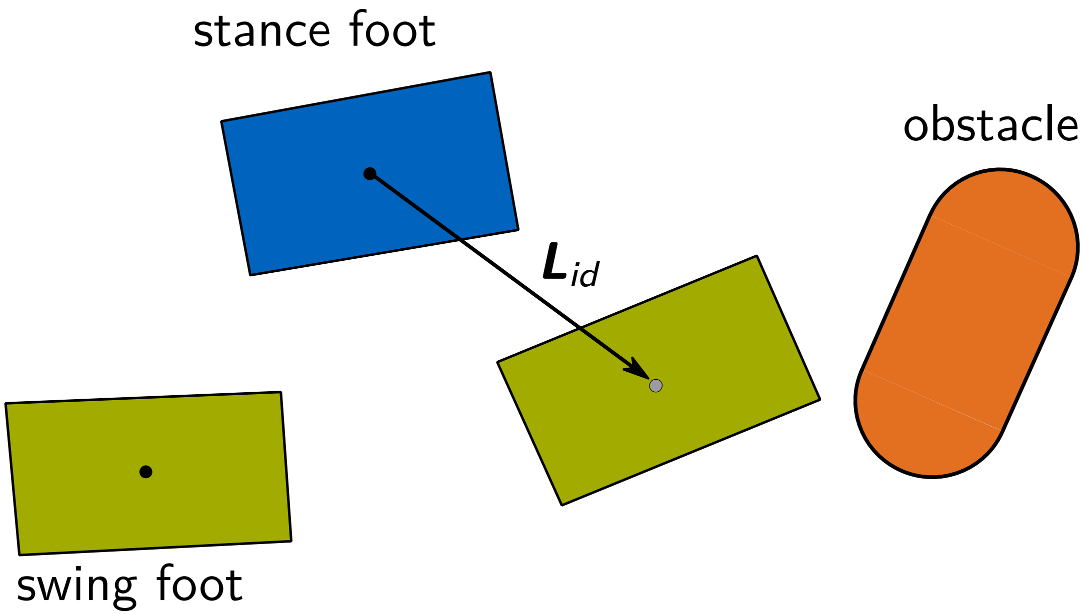
receeding horizon for CoG modification:



Combination with collision avoidance

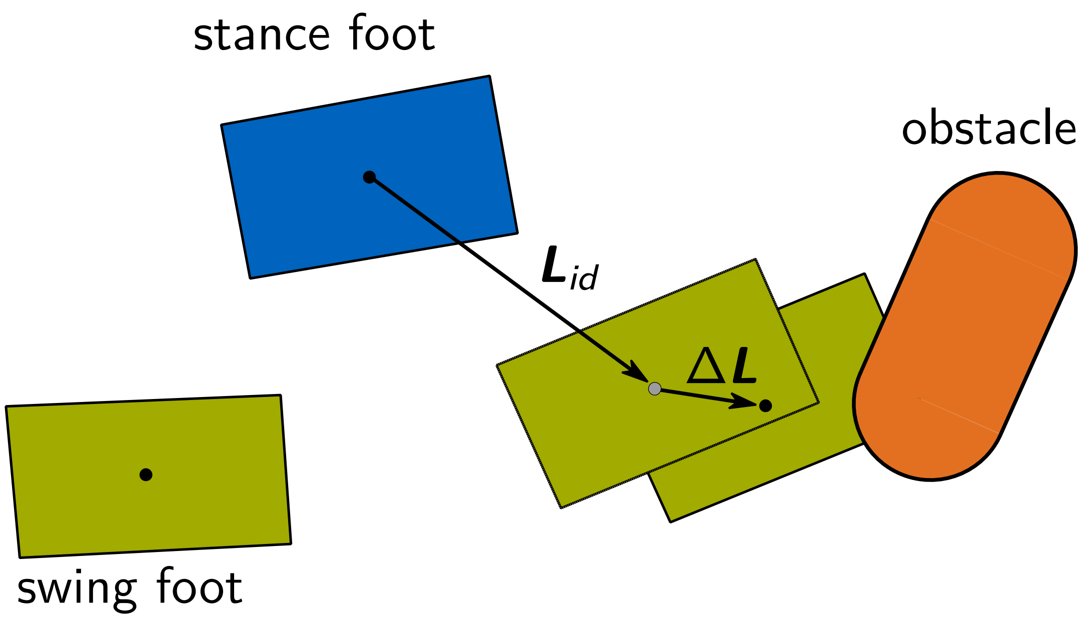
Vision + planning + stabilization?

Problem Description



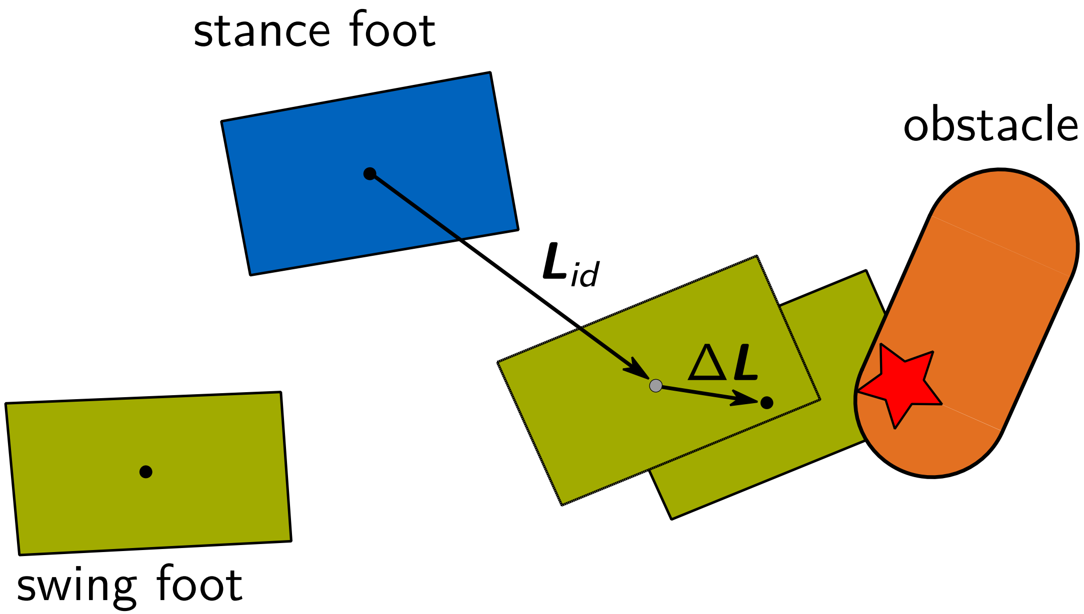
- $\boldsymbol{L}_{id}$: ideal step

Problem Description



- $\boldsymbol{L}_{id}$: ideal step
- $\Delta \boldsymbol{L}$: adaptation (disturbance)

Problem Description



- $\boldsymbol{L}_{id}$: ideal step
- $\Delta \boldsymbol{L}$: adaptation (disturbance)
- $\boldsymbol{L}_{id} + \Delta \boldsymbol{L}$: collision!

Strategy

- preserve hierarchy
- collision avoidance $>$ stabilization

Strategy

- preserve hierarchy
- collision avoidance $>$ stabilization
- foot position in optimization:

$$p \in \mathcal{P}$$

Optimization (again)

$$\begin{aligned} \min_{u,p} \, & J(u,p) \\ \dot{\boldsymbol{x}} &= \boldsymbol{f}(\boldsymbol{x}, u, p) \\ \boldsymbol{x}(t_0) &= \boldsymbol{x}_0 \\ u &\in \mathcal{U} \\ & \boxed{p \in \mathcal{P}} \end{aligned}$$

Strategy

- preserve hierarchy
- collision avoidance $>$ stabilization
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- question:

$$\mathcal{P} = ??$$

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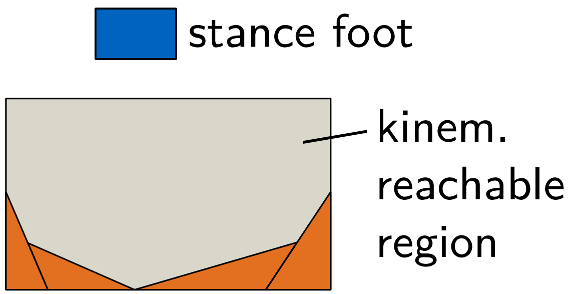
$\Rightarrow$ geometric constraints $\rightarrow$ inequality constraints

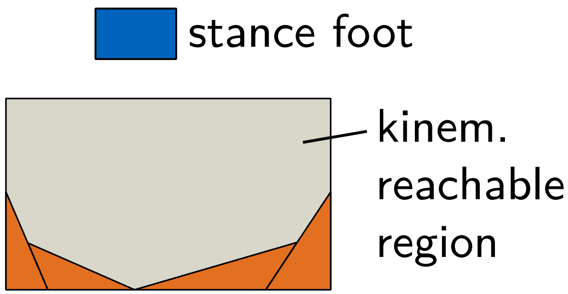
Geometric Constraints

kinematic limits

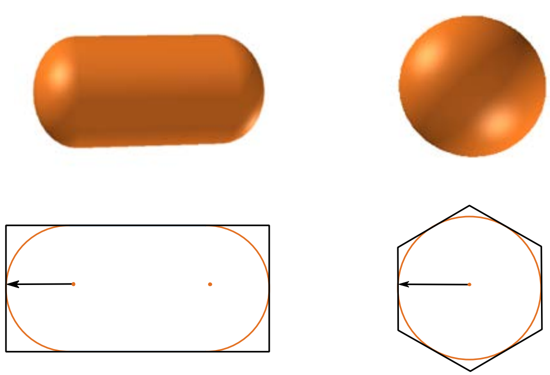


Geometric Constraints

kinematic limits

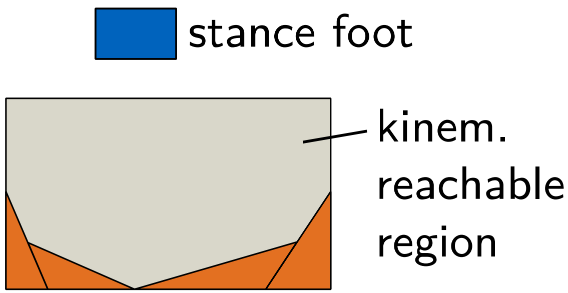


obstacles

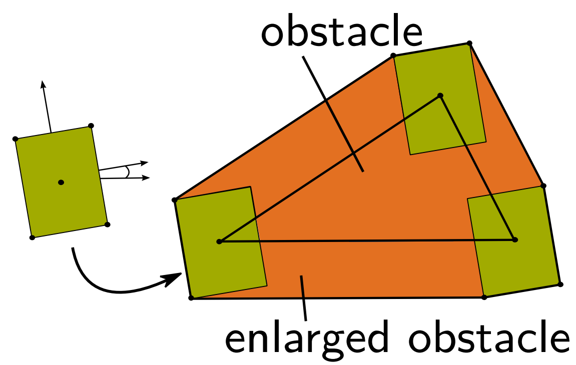


Geometric Constraints

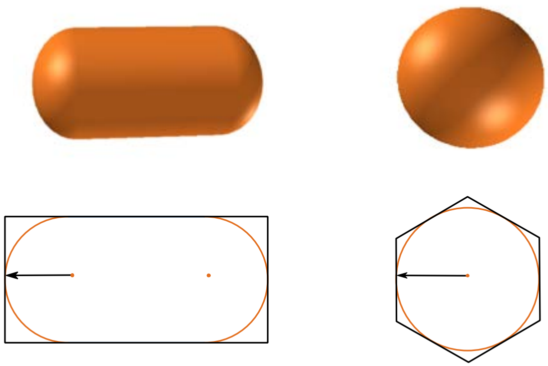
kinematic limits



foot geometry

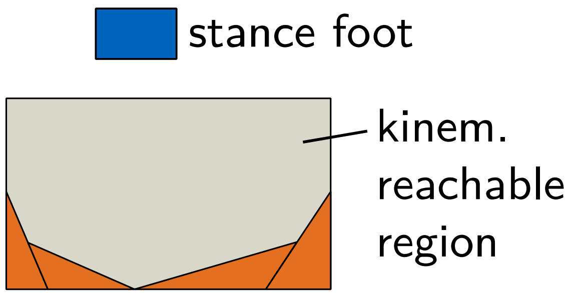


obstacles

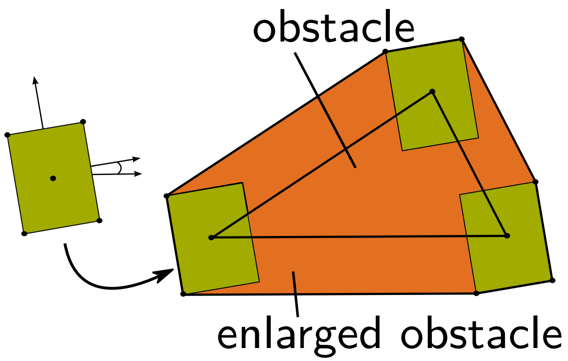


Geometric Constraints

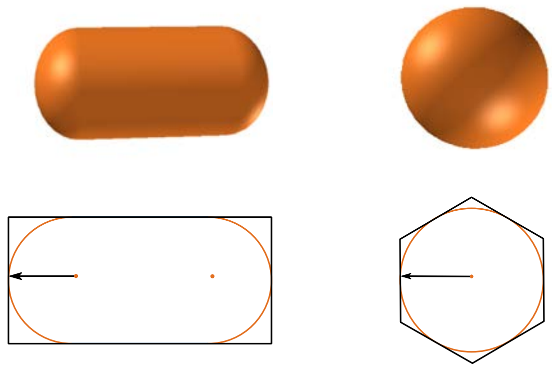
kinematic limits



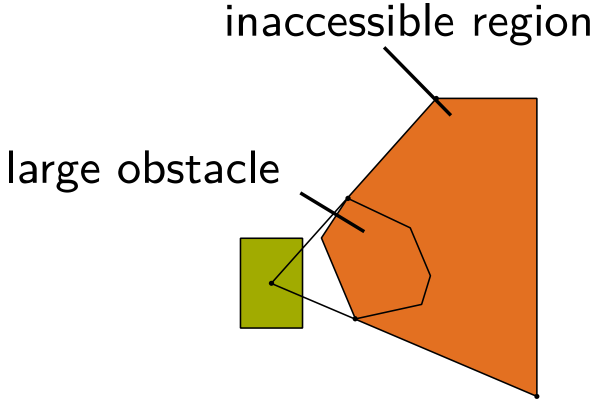
foot geometry



obstacles



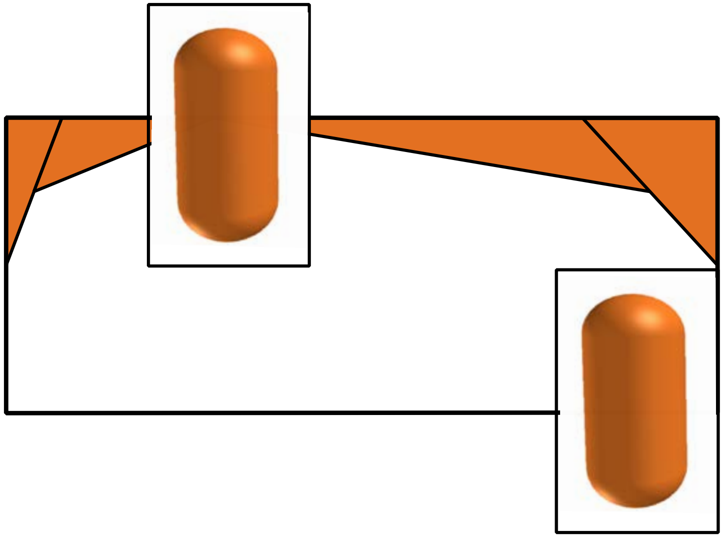
large obstacles



Finding Safe Footholds

- set of all inequality constraints
- invalid points $\boldsymbol{x}$:

$$\mathcal{C}_{I,k} = \boldsymbol{A}_k \boldsymbol{x} > \boldsymbol{b}_k$$



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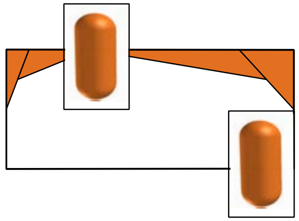
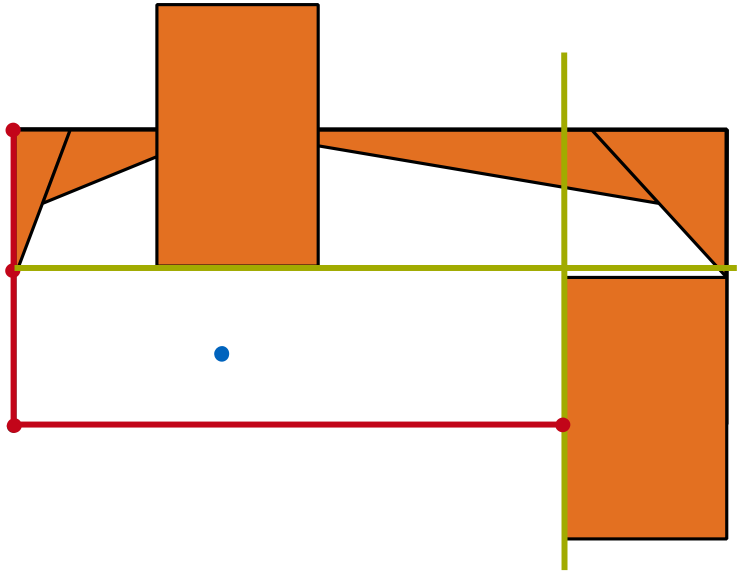


- search safe regions with different seed points



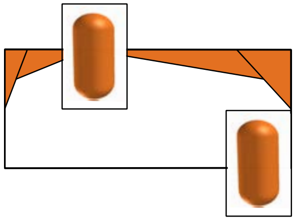
Finding Safe Footholds

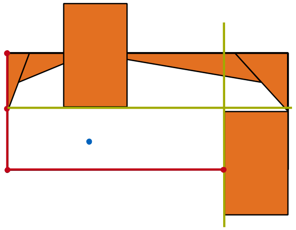
- set of all inequality constraints
- invalid points $\boldsymbol{x}$:

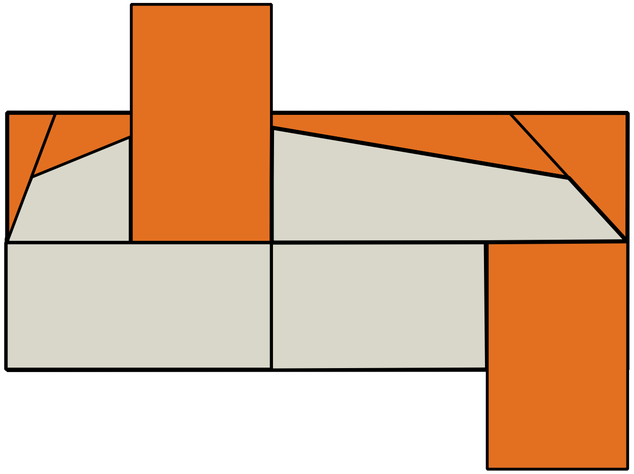
$$\mathcal{C}_{I,k} = \boldsymbol{A}_k \boldsymbol{x} > \boldsymbol{b}_k$$

- search safe regions with different seed points
- set of convex safe regions

$$\mathcal{P} = \{\mathcal{C}_{V,1}, \ldots \mathcal{C}_{V,n}\}$$







Finding Safe Footholds

- set of all inequality constraints
- invalid points $\boldsymbol{x}$:

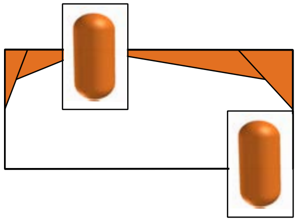
$$\mathcal{C}_{I,k} = \boldsymbol{A}_k \boldsymbol{x} > \boldsymbol{b}_k$$

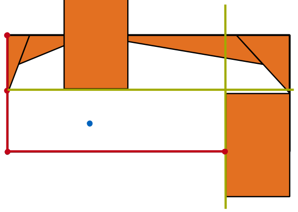
- search safe regions with different seed points
- set of convex safe regions

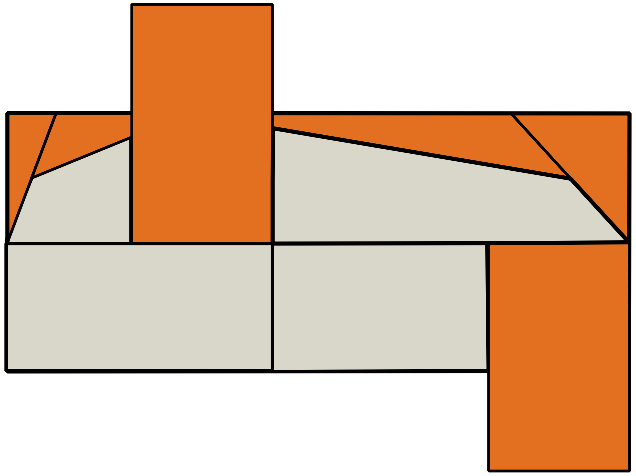
$$\mathcal{P} = \{\mathcal{C}_{V,1}, \ldots \mathcal{C}_{V,n}\}$$

- compute closest point

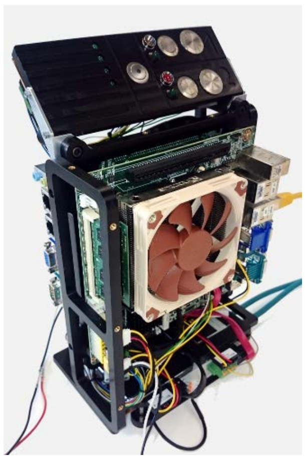
$$p \in \mathcal{P}$$





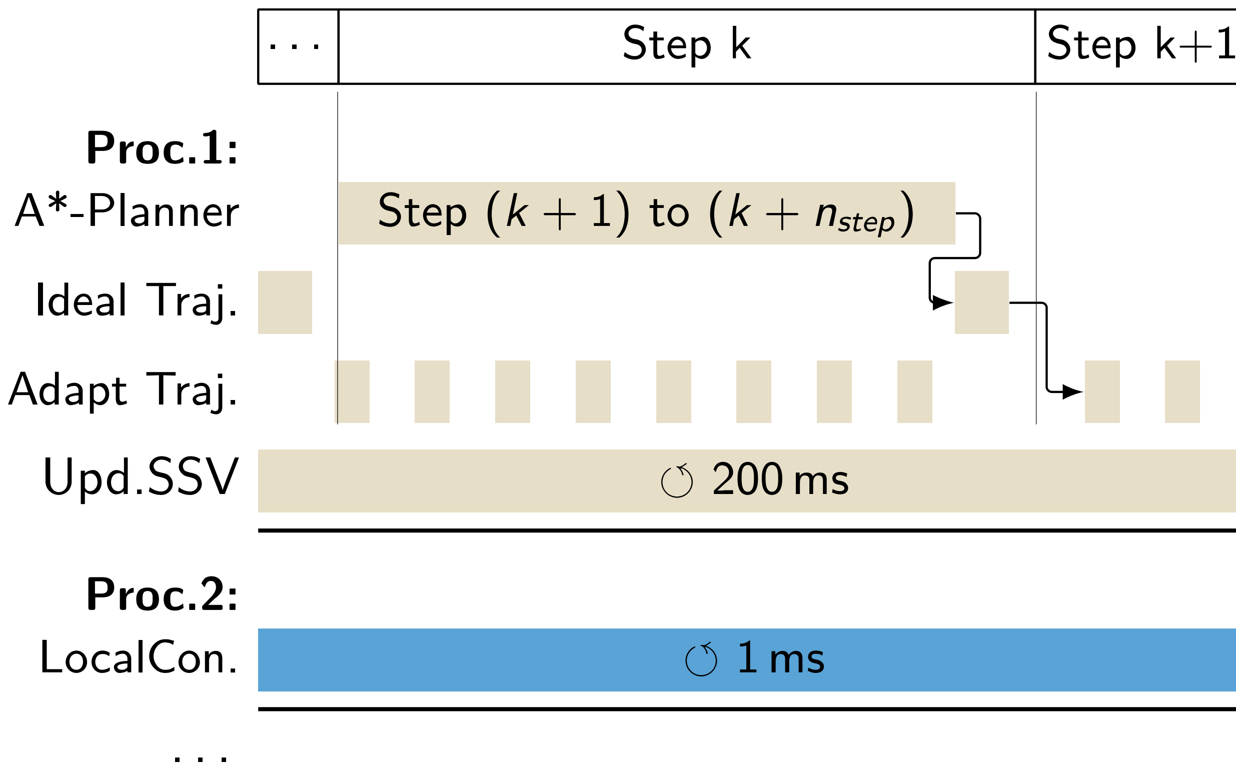


Real-time System

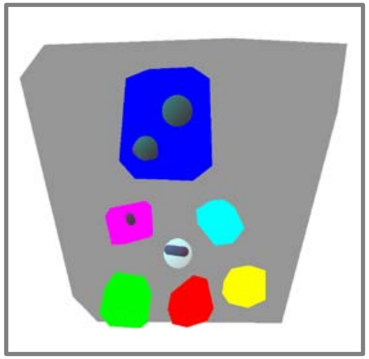


Onboard computer (2x Intel i7)

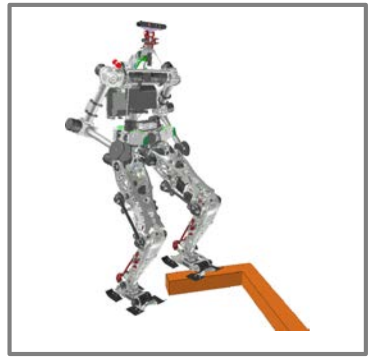
- 1x Linux (vision)
- 1x QNX (control)



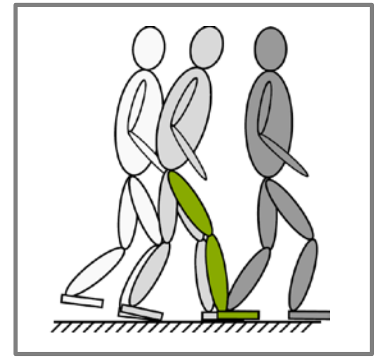
Summary



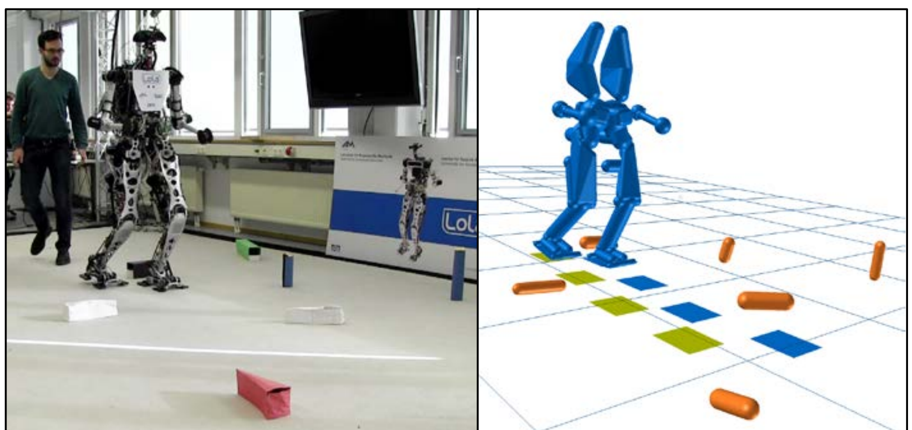
Environment Modeling



Motion Generation



Stabilization



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Environment Modeling

Vision System

Navigation and Motion Generation

Stabilization

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Limitations

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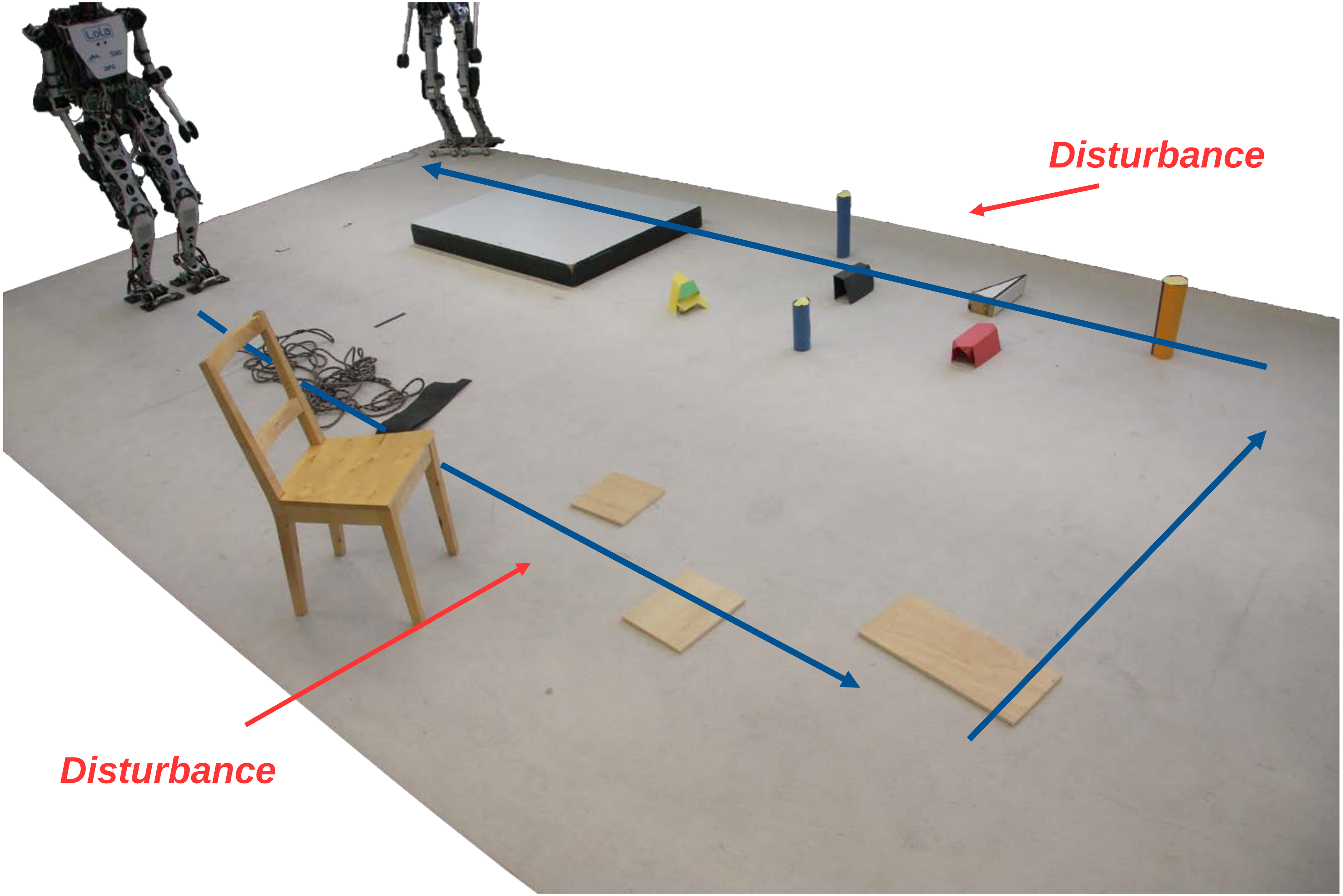

Disturbance
Disturbance

Results

Videos can be found at:

www.youtube.com/appliedmechanicstum

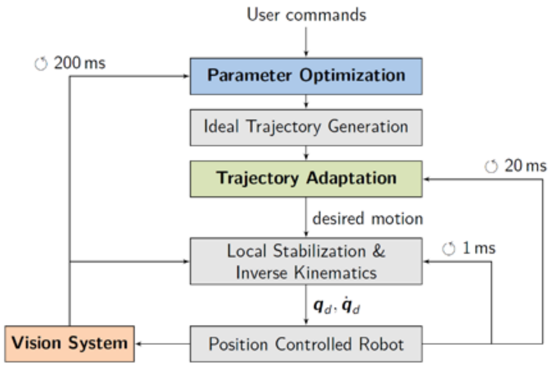
Lola – Playlist

https://www.youtube.com/playlist?list=PLVAvoOVYkpkMFNgz8cercTVvVryz1eh0a

Limitations

Hardware:

- Prototype state
- Cabling issues
- Camera accuracy
- Rare communication errors



Software:

- More software testing
- Advanced error handling
    - Methods fail
    - Other fails
- Robustness
- Tuning

Sources

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