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Design and Control of the BlueFoot Platform:

A Multi-terrain Quadruped Robot

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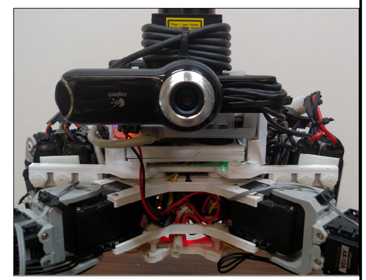
5/13/2015

NYU POLYTECHNIC SCHOOL OF ENGINEERING — Overview

Overview of Presentation

Å Introduction
Å System Design and Software
Å Model of the BlueFoot Robot
Å Gait and Stability Control
Å Navigation Control
Å Concluding Remarks



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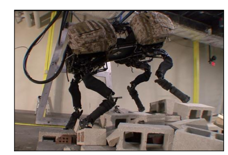
Introduction

NYU POLYTECHNIC SCHOOL OF ENGINEERING — Quadruped Robotics

Inspired by notable quadruped robotic systems from the past decade:

- LittleDog (Boston Dynamics)
- BigDog (Boston Dynamics)
- HyQ (Istituto Italiano di Tecnologia)
- Tekken (Kyoto Institute of Technology)
- Kolt (Stanford University)



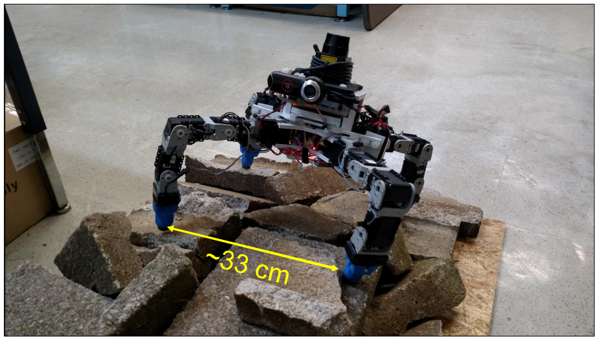
- **Relevant Research Areas:**
  - Gaiting design
  - Rough-terrain navigation/planning
- **Example Applications:**
  - Disaster recovery
  - Search and rescue
  - Environmental mapping

BlueFoot quadruped robot is designed to be:

- Small scale and compact
- Dexterous (16 actuated degrees of freedom)
  - Stabilize and reposition on variable terrain
  - Large range of trunk articulation
  - Ability to overcome raised/uneven terrain
- Capable from a computational and sensory standpoint

Particular elements achieved in design are as follows:

- 2.0+ kg of payload capacity
- 30+ battery life
- Multi-processor architecture
- Large range of sensory capabilities
  - IMU, Camera, LIDAR, GPS
  - Joint position, velocity, loading sensing (using smart servos)
  - Foot contact sensing



Overview of motion control strategies:

- Central Pattern Generator (CPG)-based gait control
- Zero-Moment Point (ZMP) body posture control
- Virtual-Force foothold controller
- NARX-Neural Network trunk-leveling controller

Overview of navigation control strategies:

- Potential-Fields/Visual-Servoing
- Surface Reconstruction for rough terrain navigation
  - Composing 3D point clouds from 2D LIDAR scans
  - Height-map Surface Representation
  - Surface (Normal) Estimation from 3D point clouds

System Design and Software

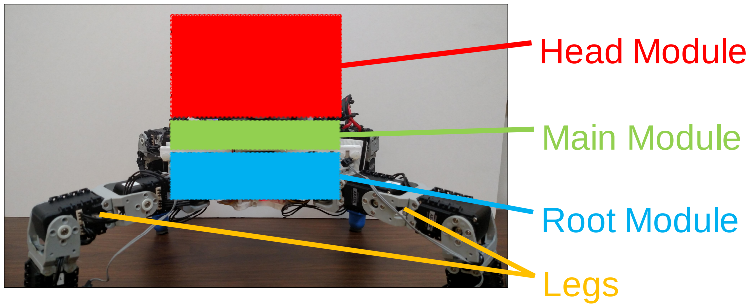
Modularity between body segments

- Robot designed with 3 main sections

3D printed structural components

- Lightweight
- Rapid design iterations
- Facilitates modular design

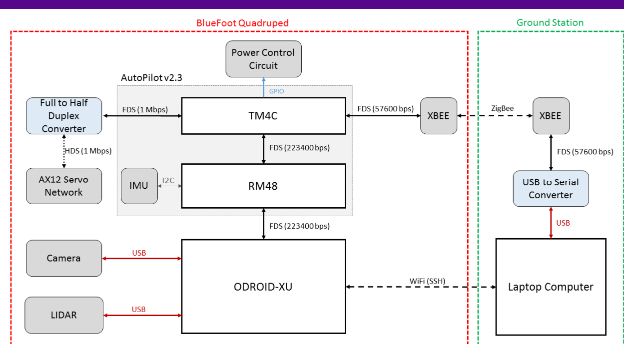
Core Devices



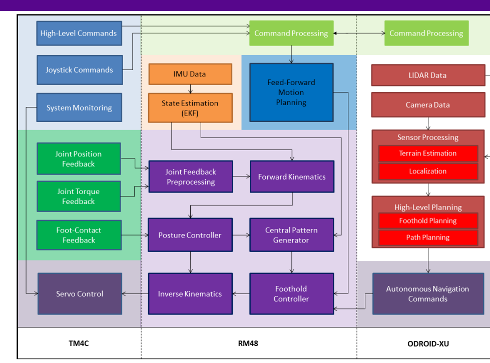
Core Devices

- AutoPilot (IMU, pressure sensor, temperature sensor)
- ODROID-XU computer
- Logitech9000 Web Camera
- Hokuyo-URG LIDAR
- Dynamixel AX12 Smart Servos (x16)
- Binary foot-contact sensors
- XBEE Wireless Radio
- GPS

Core Devices



Core Devices



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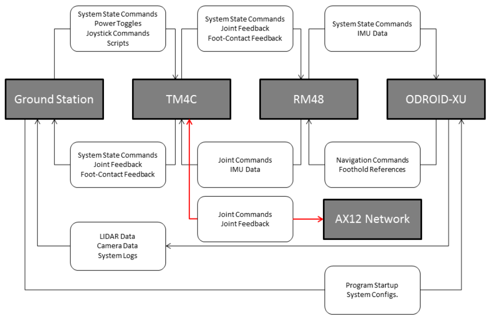


BlueFoot: Kinematic and Dynamical Modeling

State Representation

Considering the robot as a free-floating system with 4 legs (each 4-DOF):

$$\eta = [p_b^T, \theta_b^T, q^T]^T$$

Trunk Position $p_b \in \mathcal{R}^3$

Trunk Orientation $\theta_b \in \mathcal{R}^3$

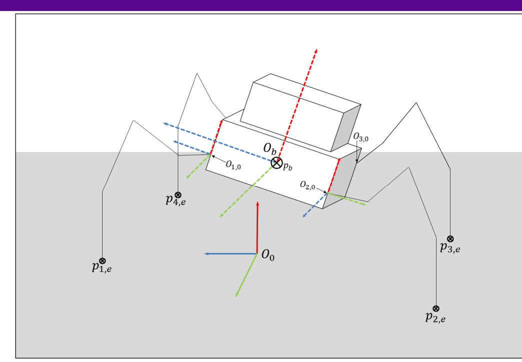
Joint angles $q \in \mathcal{R}^{16}$

Gives rise to the following state vector:

$$z = [\eta^T, \dot{\eta}^T]^T \in \mathcal{R}^{44}$$

$$z_1 = \eta \qquad z_2 = \dot{\eta}$$

Coordinate Frame Setup



Forward Kinematics

First leg frame with respect to world frame O_0:

$$H_0^{i,0} = \left[\begin{array}{c|c} R_{zyx}(\theta_b)R_z(\sigma_i) & R_{zyx}(\theta_b)\vec{\beta}_i + p_b \\ \hline 0 & 1 \end{array}\right] \qquad \begin{aligned} \sigma_i &= \tfrac{\pi}{2}(i-1) + \tfrac{\pi}{4} \\ \vec{\beta}_i &= R_z(\sigma_i)\vec{o}_\nu \\ \vec{o}_\nu &= [\nu, 0, 0]^T \end{aligned}$$

General transformation to each j^{th} joint from the 1st frame of attached to each i^{th} leg:

$$H_{i,j}^{i,0} = \left[\begin{array}{c|c} R_{i,j}^{i,0} & p_{i,j}^{i,0} \\ \hline 0 & 1 \end{array}\right]$$

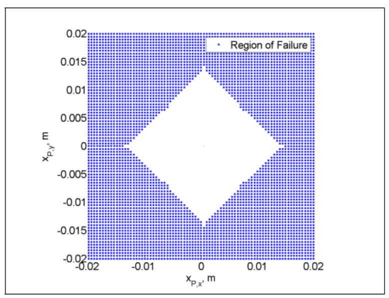
Inverse Kinematics

Joint configuration solution for the i^{th} leg, given $p_{i,e}$ and γ_i:

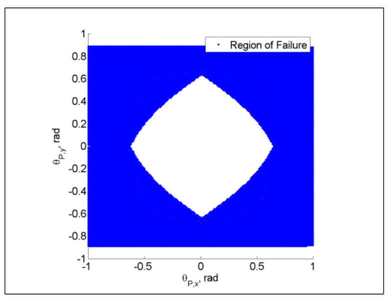
$$\begin{aligned} q_{i,1} &= \cos(i\pi)\left(\frac{\pi}{4} - \psi_i\right) \\ q_{i,2} &= \tan^{-1}\left(\frac{\zeta_{i,z}}{\sqrt{\zeta_{i,x}^2 + \zeta_{i,y}^2}}\right) \mp \cos^{-1}\left(\frac{a_3^2 - a_2^2 - \|\zeta_i\|^2}{2a_2\|\zeta_i\|}\right) \pm \pi \\ q_{i,3} &= \mp\cos^{-1}\frac{\|\zeta\|^2 - a_2^2 - a_3^2}{2a_2a_3} \\ q_{i,4} &= \boxed{\gamma_i} - q_{i,2} - q_{i,3} \end{aligned}$$

Ankle configuration

Kinematic Limits on Trunk Pose



Trunk position (x,y)



Orientation (roll and pitch)

Dynamics

Dynamics of the system takes the following form:

$$M(\eta)\ddot{\eta} + C(\eta,\dot{\eta})\dot{\eta} + G(\eta) + \boxed{\Delta H} = \tau + J^T(\eta)f_{ext}$$

Lump disturbance term

$$\tau = [0_{1x6}, \tau_q^T]^T$$

In state-space form:

$$\begin{aligned} \dot{z}_1 &= z_2 \\ \dot{z}_2 &= M^{-1}(z_1)(\tau + \Phi(z_1, z_2, f_{ext})) \\ \Phi(z_1, z_2, f_{ext}) &= J^T(z_1)f_{ext} - C(z_1,z_2)z_2 - G(z_1) - \Delta H \end{aligned}$$

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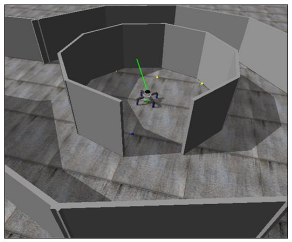
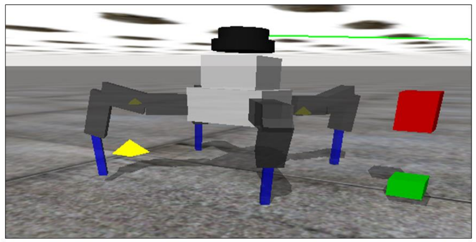
Dynamics Simulator





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Dynamics Simulator

BlueFoot Simulator implemented using the *Open Dynamics Engine* C++ library

- Generates dynamical updates for all bodies via constrained quadratic minimization
- Rigid body and contact dynamics formulated as a Linear Complimentary problem (LCP)
- First-order integration with small time-step ($\Delta t \ll 1$)

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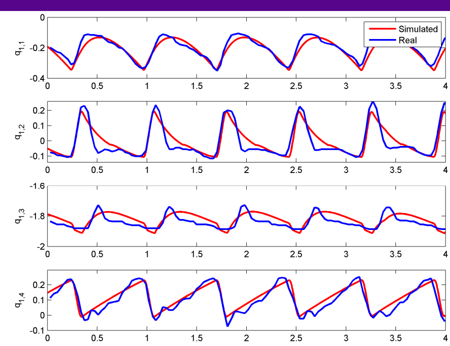
Dynamics Simulator



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Gaiting and Stability Control

Central pattern generators

- Network of limit-cycle oscillators (unit-oscillators)
  - Hopf oscillators are used in this implementation
- Tunable coupling
  - Particular tuning of coupling generates phase-locked loops, which are applied to driving robot DOFs

Each i^{th} unit oscillator has a state-pair

$$\{y_{1,i}, y_{2,i}\}$$

The full CPG network dynamics are

$$\begin{aligned}\dot{y}_1 &= A_1\left(\Psi_M M\left(y_1, y_2\right) - \Gamma\right) y_1 + \Psi_\omega W y_2 \\ \dot{y}_2 &= A_2\left(\Psi_M M\left(y_1, y_2\right) - \Gamma\right) y_2 - \Psi_\omega W y_1 + K y_2\end{aligned}$$

with

$$M\left(y_1, y_2\right) = \begin{bmatrix} y_{1,1}^2 + y_{2,1}^2 & 0 & 0 & 0 \\ 0 & y_{1,2}^2 + y_{2,2}^2 & 0 & 0 \\ 0 & 0 & y_{1,3}^2 + y_{2,3}^2 & 0 \\ 0 & 0 & 0 & y_{1,4}^2 + y_{2,4}^2 \end{bmatrix}$$

Reflexes are designed using modulation parameters:

$$\begin{aligned}\Psi_\omega &= I + A_\omega \mathrm{diag}\left(\psi_i\right) \\ \Psi_M &= I - A_\mu \mathrm{diag}\left(\psi_i\right) \\ \psi_i &= \mathrm{sig}\left(w_i v_i - w_i c_i\right) \mu_i\end{aligned}$$

Coupling matrices used for gaiting the BlueFoot Platform:

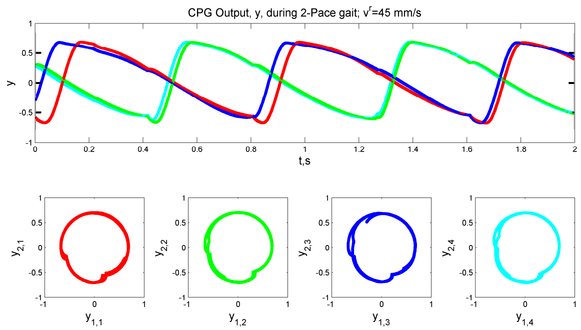
$$K \equiv \begin{bmatrix} 0 & -1 & 1 & -0.5 \\ -1 & 0 & -0.5 & 1 \\ -1 & -0.5 & 0 & -1 \\ -0.5 & 1 & -1 & 0 \end{bmatrix}$$

Produces 4-Pace Walking Gait

$$K \equiv \begin{bmatrix} 0 & -1 & 1 & -0.5 \\ -1 & 0 & -0.5 & 1 \\ -1 & 0.5 & 0 & -1 \\ 0.5 & -1 & -1 & 0 \end{bmatrix}$$

Produces 2-Pace Trotting Gait

Central Pattern Generators (CPG)



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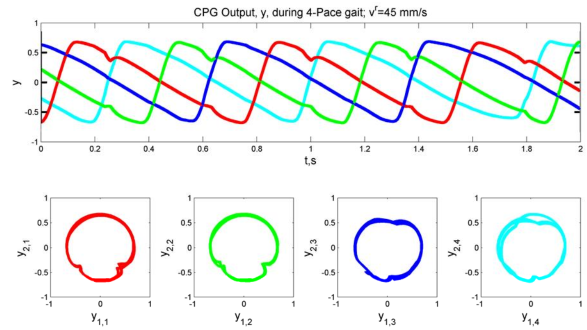
Central Pattern Generators (CPG)



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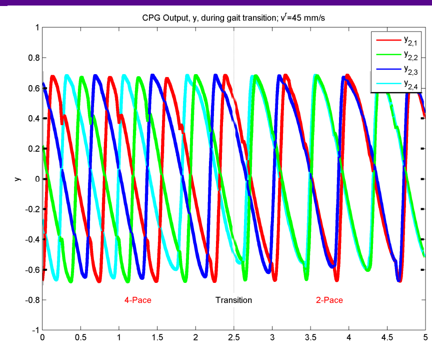
Central Pattern Generators (CPG)



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Foothold Control

Reference velocity of each foot is controlled by:

$$\dot{p}^r_{i,e} = \dot{\tilde{p}}^v_{i,e} + \dot{\tilde{p}}^y_{i,e}$$

with

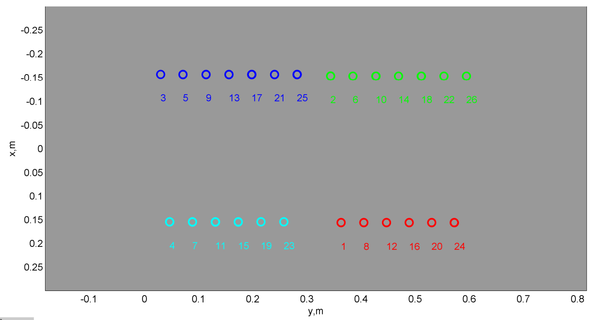
$$\dot{\tilde{p}}^v_{i,e} = \frac{1}{m_i}\int^t P_{\vec{h}_i}\left(F_{s,i} - b_c \dot{p}_{i,e} + F_{\epsilon,i}\right) d\tau$$

$$F_{s,i} = k_c\left(\tilde{p}_{i,e} - p_{i,e}\right) U(y_{2,i})$$

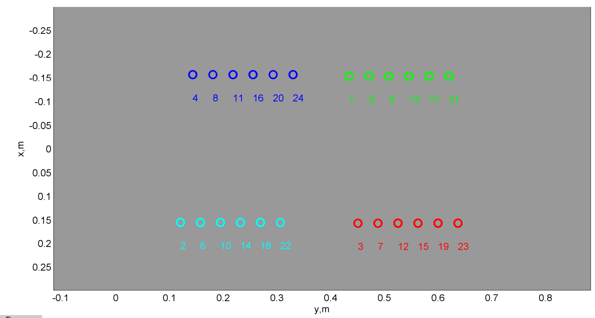
$$F_{\epsilon,i} = a_\epsilon \dot{\epsilon}_\theta U(y_{2,i})$$

$$\dot{\tilde{p}}^y_{i,e} = \left(\alpha_v v^r + \alpha_\omega \|\omega^r\|\right) \dot{y}_{2,i} \vec{h}_i$$

Foothold Control



Foothold Control



ZMP Body Control

Zero Moment Point (ZMP) Control

- Zero Moment Point is a point beneath the robot at which the net moment on robot body is zero
- Control robots center of gravity to reduce angular velocity of the trunk during gaiting (using trunk)

ZMP Body Control

ZMP computed by:

$$p^{b'}_{ZMP} = R_{z_P}\left(\frac{\pi}{2}\right)\left(\frac{\|g\|}{m_b}\right)\tau_{legs} + \hat{p}^{b'}_{COG}$$

Body reference position controlled by:

$$\dot{p}^{b',r}_{b} = P_{\tilde{h}_i}\left(K_Z(p^{b'}_{ZMP} - p^{b'}_{b}) + K_F\frac{F_r}{m_b}\right)$$

$$\begin{aligned} F_r &= \sum_{i=1}^{4} e^{(k_l r_i^-)} + e^{(k_l r_i^+)} \\ r_i^+ &= \left\|p^{b'}_{i,e} - p^{b'}_{b}\right\| - r_{max} \\ r_i^- &= r_{min} - \left\|p^{b'}_{i,e} - p^{b'}_{b}\right\| \end{aligned}$$

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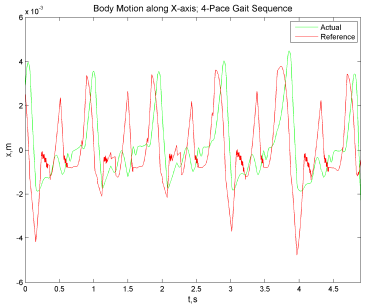
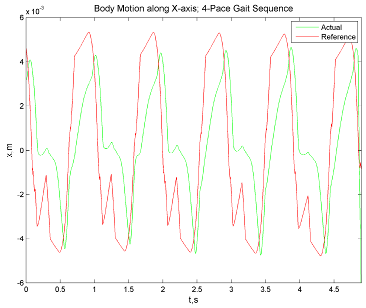
ZMP Body Control





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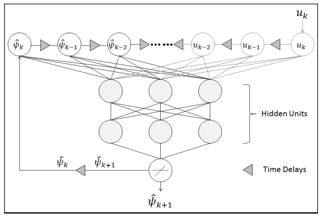
NARX-NN Trunk Leveling Controller

NARX-Neural Network (NARX-NN)

Used to capture periodic disturbance dynamics during gaiting

$$\begin{aligned} \hat{\psi}_{k+1} &= \mathcal{N}(\hat{\Psi}_k^N, U_k^N) \\ \hat{\Psi}_k^N &= [\hat{\psi}_k, \hat{\psi}_{k-1}, \ldots, \hat{\psi}_{k-N+1}] \\ U_k^N &= [u_k, u_{k-1}, \ldots, u_{k-N+1}] \end{aligned}$$

$$u_k = (z_{1,k}, z_{2,k}, f_{ext,k})$$



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NARX-NN Trunk Leveling Controller

Isolate trunk dynamical subsystem:

$$\ddot{\theta}_b = \Gamma_1 M^{-1}(z_1)(\Gamma_2 \tau_q + \Phi) \qquad \ddot{\theta}_b = -K_b\theta_b - K_d\dot{\theta}_b$$

Estimate corrected torque using NARX-NN prediction:

$$\hat{\tau}_{q,k} = -\left[\Gamma_1 \hat{M}_{1,k}^{-1}\Gamma_2\right]^{\dagger}\left[\Gamma_1 \hat{M}_{1,k}^{-1}\hat{\psi}_{k+1} + K_b\theta_{b,k} + K_d\dot{\theta}_{b,k}\right]$$

Generate corrected joint reference from inverted actuator dynamics:

$$\boxed{\tau_q = k_s(q^r - q)} \longrightarrow q_{1,k}^{r,*} = k_s^{-1}(\hat{\tau}_{q,k}) + q_{1,k}$$

$$\tilde{q}_k^r \leftarrow (1-\alpha)q_k^r + \alpha(q_k^{r,*})$$

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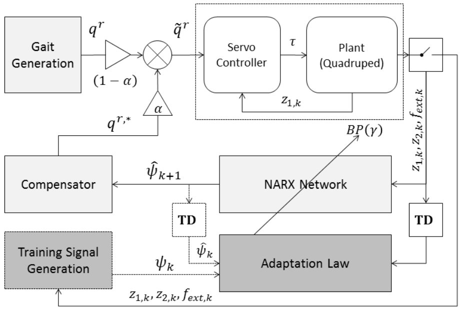
NARX-NN Body Leveling Controller



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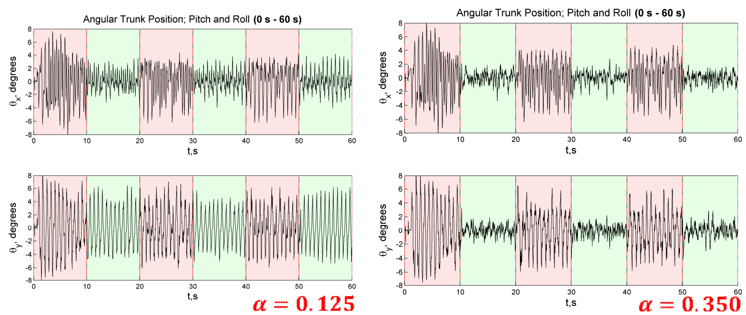
NARX-NN Trunk Leveling Controller



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NARX-NN Trunk Leveling Controller

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Navigation Control

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Potential Fields/Visual-Servoing

LIDAR-Based Potential Fields

- Virtual forces generated from points of interest (obstacles) sensed using distance sensor (LIDAR).
- Forces guide the robot around obstacles

Image-Based Visual Servoing

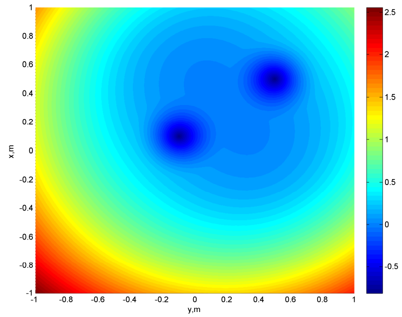
- Features (targets) extracted from images
- Robot is tracks features by gaiting and articulating its trunk
- Used to make the robot track a ñleaderò

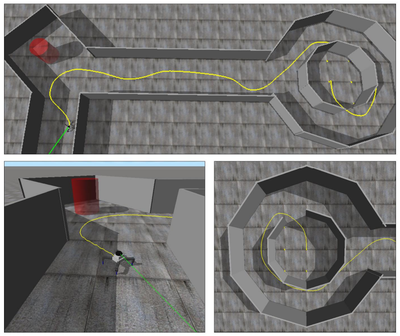
Potential Fields Formulation

$$
\begin{aligned}
\vec{u}^{r}_{L} &= \sum_{x_i^L \in S^L} g_{\psi}(x_i^L) f(x_i^L) \frac{x_i^L}{\|x_i^L\|} \\
P_L &= \alpha_p \sum_{x_i^L \in S^L} g_{\psi}(x_i^L) f(x_i^L) U\left(f(x_i^L)\right)
\end{aligned}
$$

Potential function:

$$
\begin{aligned}
\Delta d &= \|x\| - d_{min} \\
f(x) &= \begin{cases} -\lambda_{c,1}\left(\Delta d\right)^2 & \text{if } \Delta d < 0 \\ (\Delta d)\left(1 - e^{-\lambda_{c,2}(\Delta d)^2}\right) & \text{otherwise} \end{cases}
\end{aligned}
$$





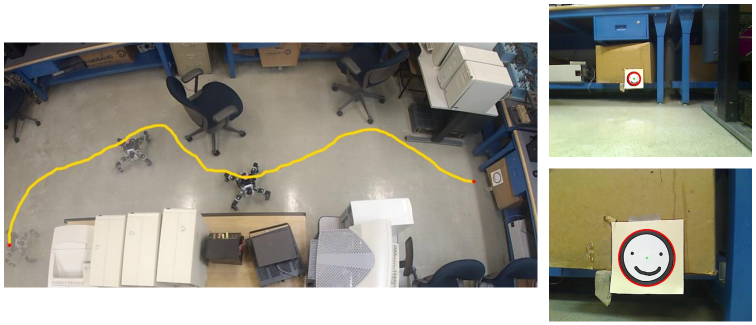
Feature extractor (blobs, circle, etc.) used to find feature locations:

$$
p_{Im} = [u, v]^T
$$

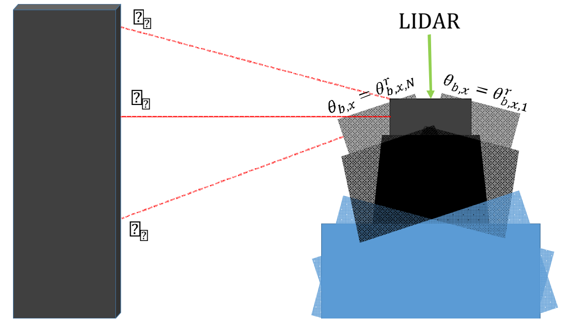
Visual servoing controller using feature location:

$$
\begin{aligned}
v^r_C &= v^{r,max}_C \left(1 - e^{-c_r(r - r_{min})^2}\right) \\
\omega^r_C &= \omega^{r,max}_C \left(\frac{w_{Im} - 2u}{w_{Im}}\right) \\
\theta^r_{b,x} &= \theta^{r,max}_{b,x} \left(\frac{2v - h_{Im}}{h_{Im}}\right)
\end{aligned}
$$

Potential Fields/Visual-Servoing



3D Point Cloud Composition



3D Point Cloud Composition

Trunk pitched according to:

$$\theta^*_{b,x,k} = (\theta_{s,max} - \theta_{s,min})\left(\frac{k}{K}\right) + \theta_{s,min}$$

$$\dot{\theta}^r_{b,x} = \alpha_\theta(\theta^*_{b,x,k} - \hat{\theta}_{b,x})$$

Points are transformed and collected to form 3D cloud:

$$\begin{bmatrix} \bar{x}_{i,k} \\ 1 \end{bmatrix} = H_b^L H_0^b \begin{bmatrix} x_i^L \\ 0 \\ 1 \end{bmatrix} \forall x_i^L \in S^L \longrightarrow \bar{S} = \bigcup_{k=1}^{N_s} \bar{S}_k \quad \bar{x}_{i,k} \in \bar{S}_k$$

Surface Representation from 3D Point Clouds

Height-Map Representation

Å Region of interest is discretized

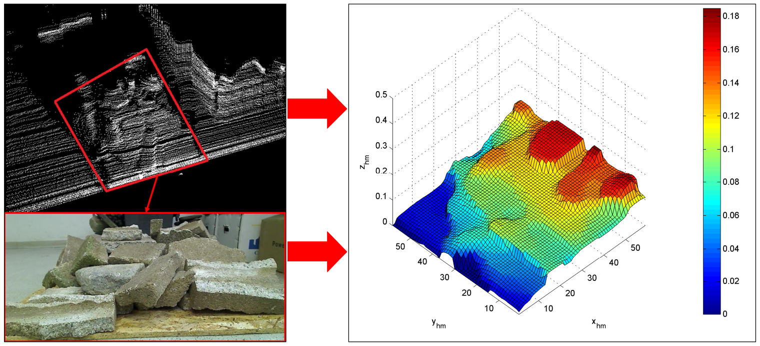
Å Heights of each sub-region are generated by averaging relative points heights (z-components in world frame)

Representation using Estimated Surface-Normals

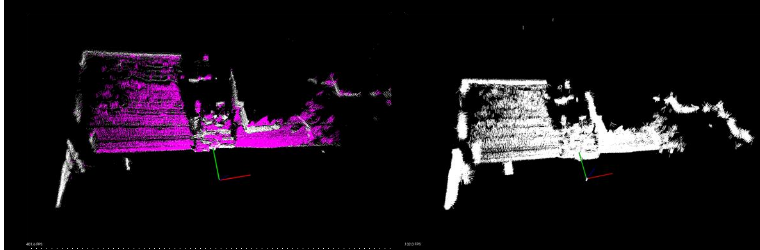
Å Plane fitting on moving subsets of points using principle component analysis technique

Å Normal emanating from each point generated to represent surface

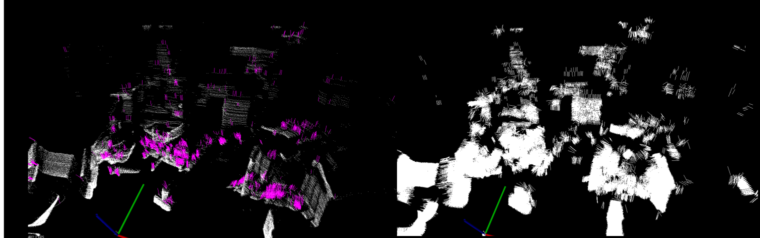
Height-Map Representation



Surface-Normal Representation



Surface-Normal Representation



Concluding Remarks

Future Directions

- Improvements to robotő actuator outfitting
- Surface maps to be used in rough-terrain planning
  - Foothold placement planning and optimization
- Prediction of terrain fitness based on few features
- Whole body motion planning for surface mapping with LIDAR/Camera during gaiting