A humanoid robot to embody Artificial Intelligence research

Arnoud Visser

NAO European Tour, CWI, Amsterdam, 16 October 2012

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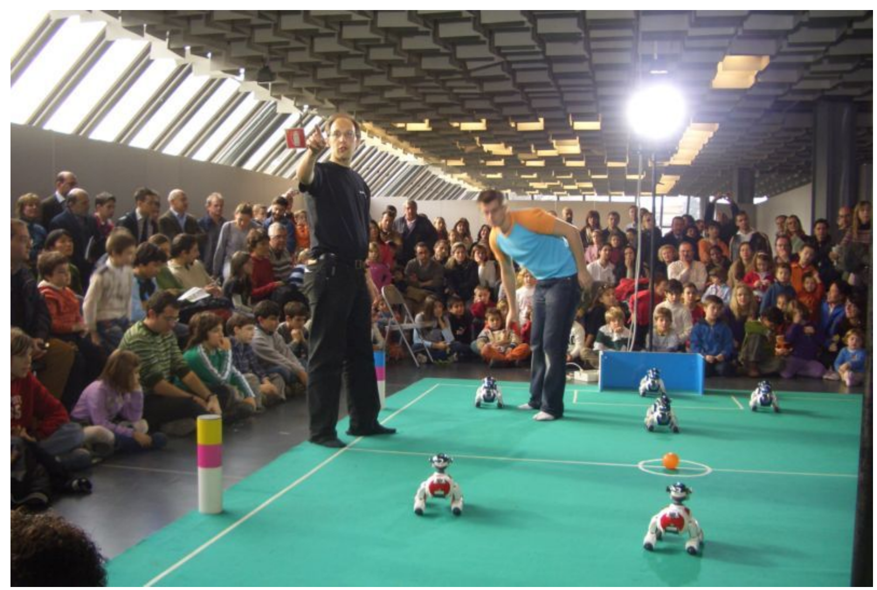
The RoboCup Challenge for the AI

By the year 2050,

develop a team of fully autonomous humanoid robots that can win against the human world soccer champion team.

Robocup World Championships



Emotion Expression of an Affective State Space;

a humanoid robot displaying a dynamic emotional state during a soccer game

Alexander van der Mey, Frank Smit, Kees-Jan Droog
and Arnoud Visser

Proc. of 3rd D-CIS Human Factors Event, p. 47-49, November 2010

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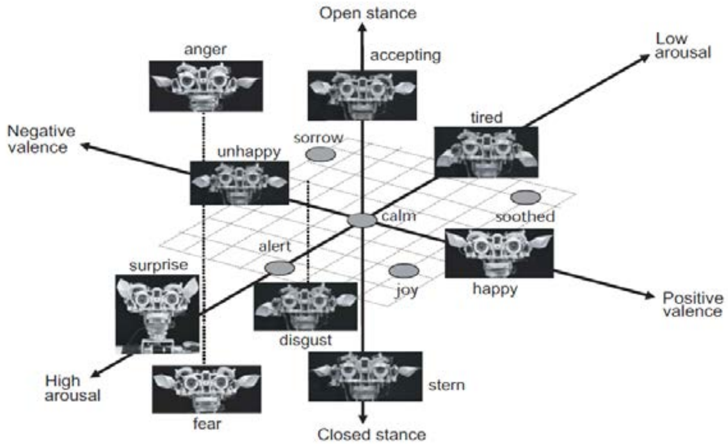
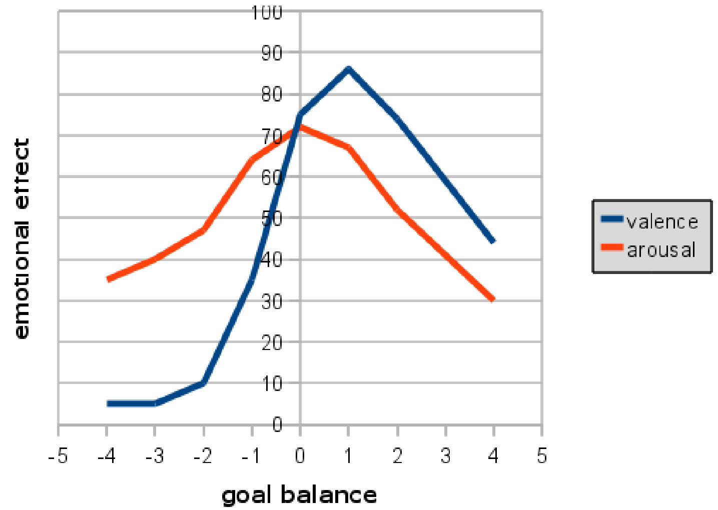
Method



Inside the scenario of watching a soccer game, identify 6 strong stimuli and map them on the affective space:

- Attempt missed (Annoyed direction | Calm direction)
- Attempt saved (Sad direction | Content direction)
- Goal (Joy direction | Angry direction)

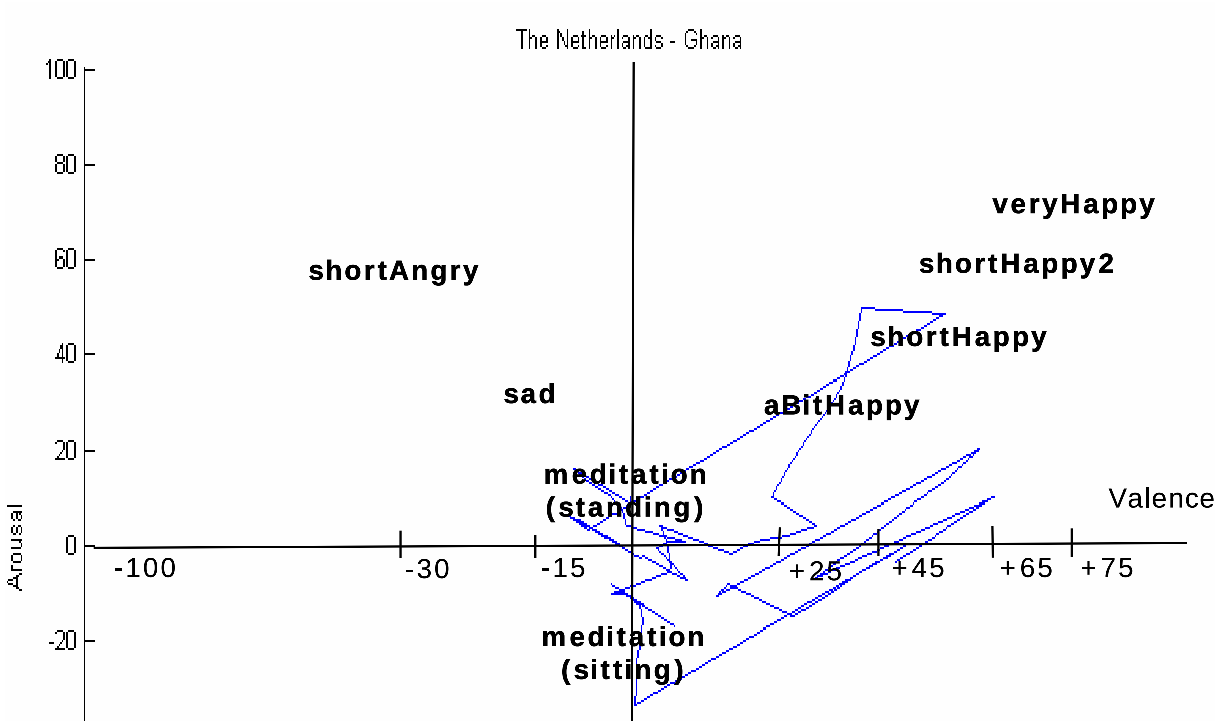
Method



The influence of the stimuli on humans is validated with a questionnaire (22 participants):

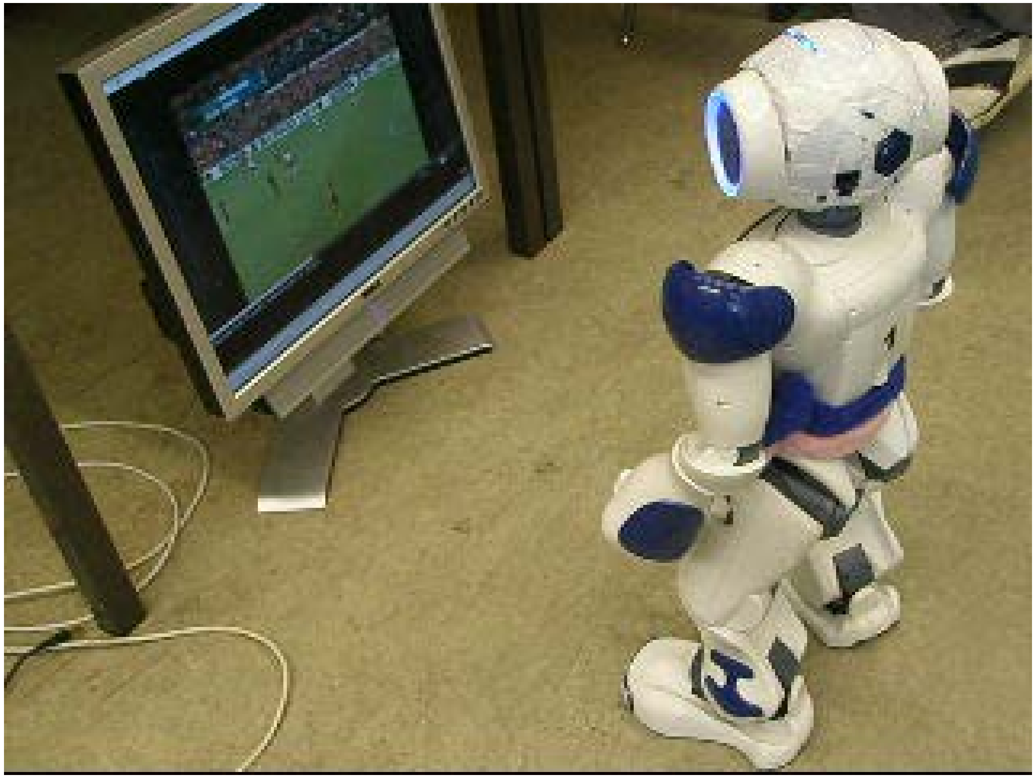
- Attempt missed (V – 20, A + 20 | V + 10, A -10)
- Attempt saved (V – 15, A - 5 | V + 15, A - 5)
- Goal (F(bgoal) | F(bgoal))

Method



Logic is added how positive and negative effects aggregate and how aggregated values fade away. Regions in the affective space are assigned to 9 Nao's emotional expressions.

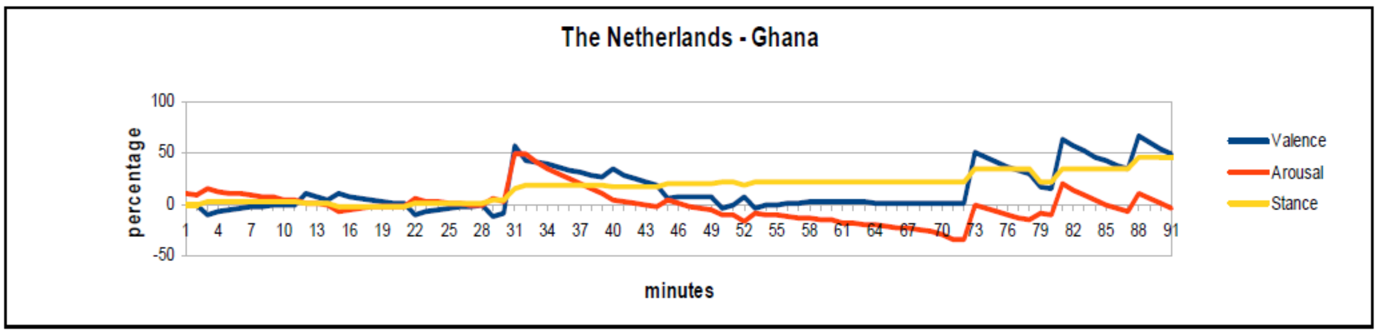
Results



Dirk Kuyt scores a goal during the soccer match
'The Netherlands-Ghana'

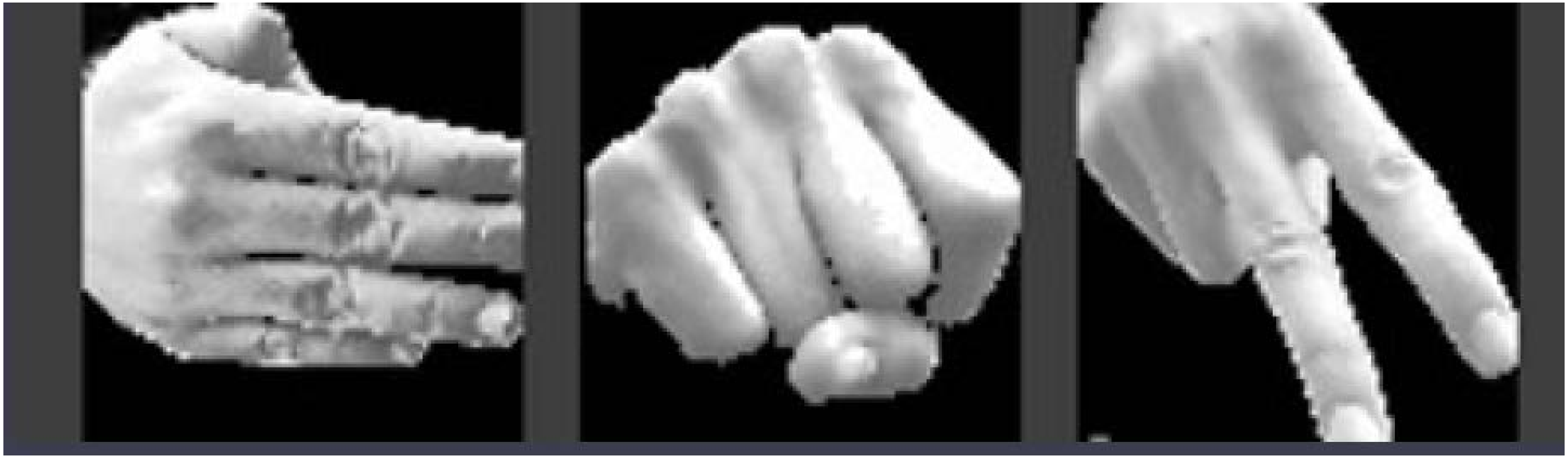
Resumé

- Emotions can be expressed by a robot, not just on stimuli-response, but on an affective state which shows dynamic behavior during the game.



- Such dynamic emotional system can enhance the interaction between robots and humans.

Rock, Paper & Scissors!



Nimrod Raiman, Silvia-Laura Pintea

Project report, June 2010

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Method

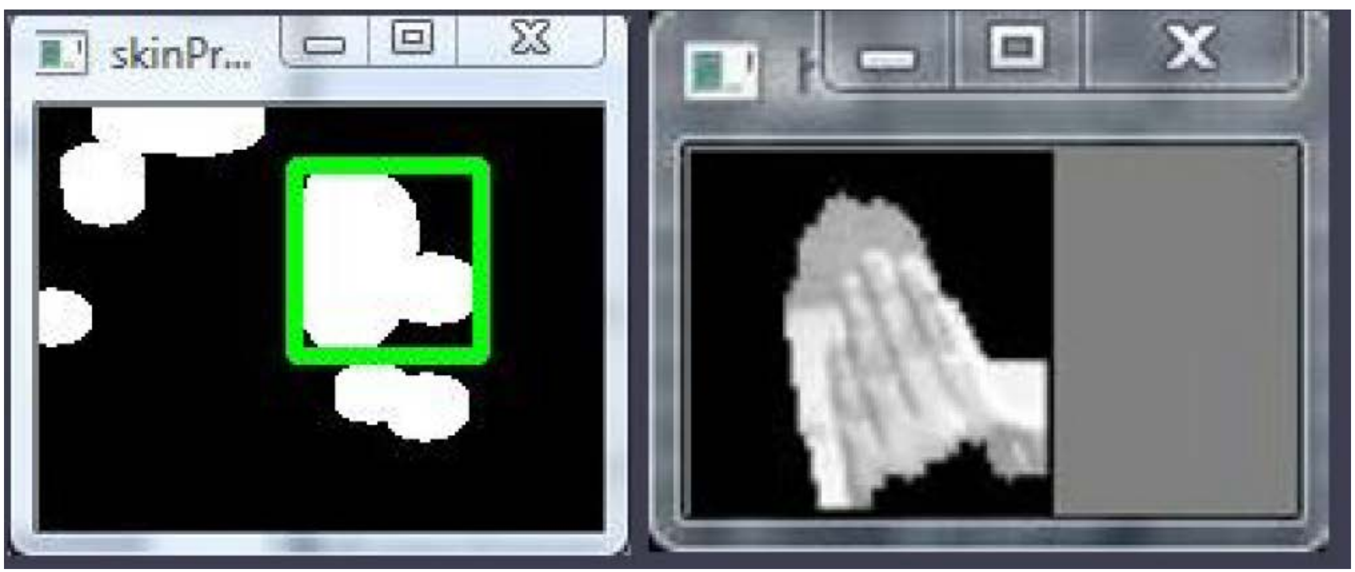
- Use face detection to detect skin color

Method

- Use color histogram to a skin probability image

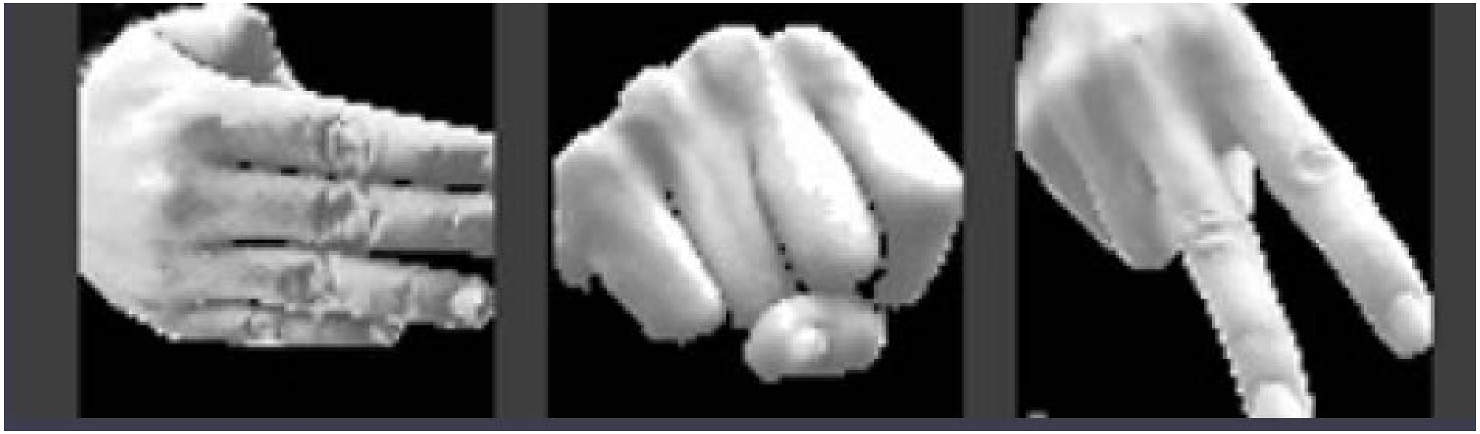
Method

- Use erosion & dilation to retain hand
- Rescale ea of interest to standard 70x70



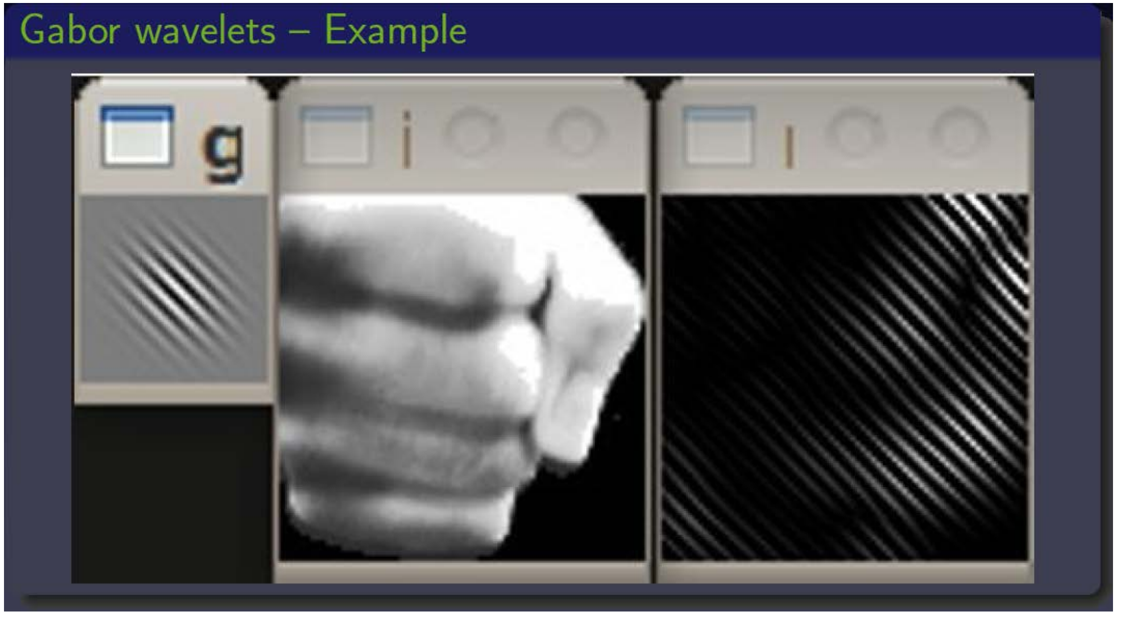
Train

- Use hands in different orientations (1400 per sign) to train eigen-hand models



Orientation independence

- The hands were convoluted with four Gabor wavelets



- The resulting 'fingerprint'-vector was classified with the K nearest neighbors technique

Resumé

Different machine learning techniques were tried:

- kNN outperformed PCA and SVN in stability
- The preprocessing highly influence the final result (1.2 % error)
- Reduction of the resolution to 20x20 reduces the sensitivity to translations

Dynamic Tree Localization

Hessel van der Molen

H. van der Molen,
“Self-localization in the RoboCup Soccer Standerd Platform League with the use of a Dynamic Tree”,
Bachelor Thesis, Universiteit van Amsterdam

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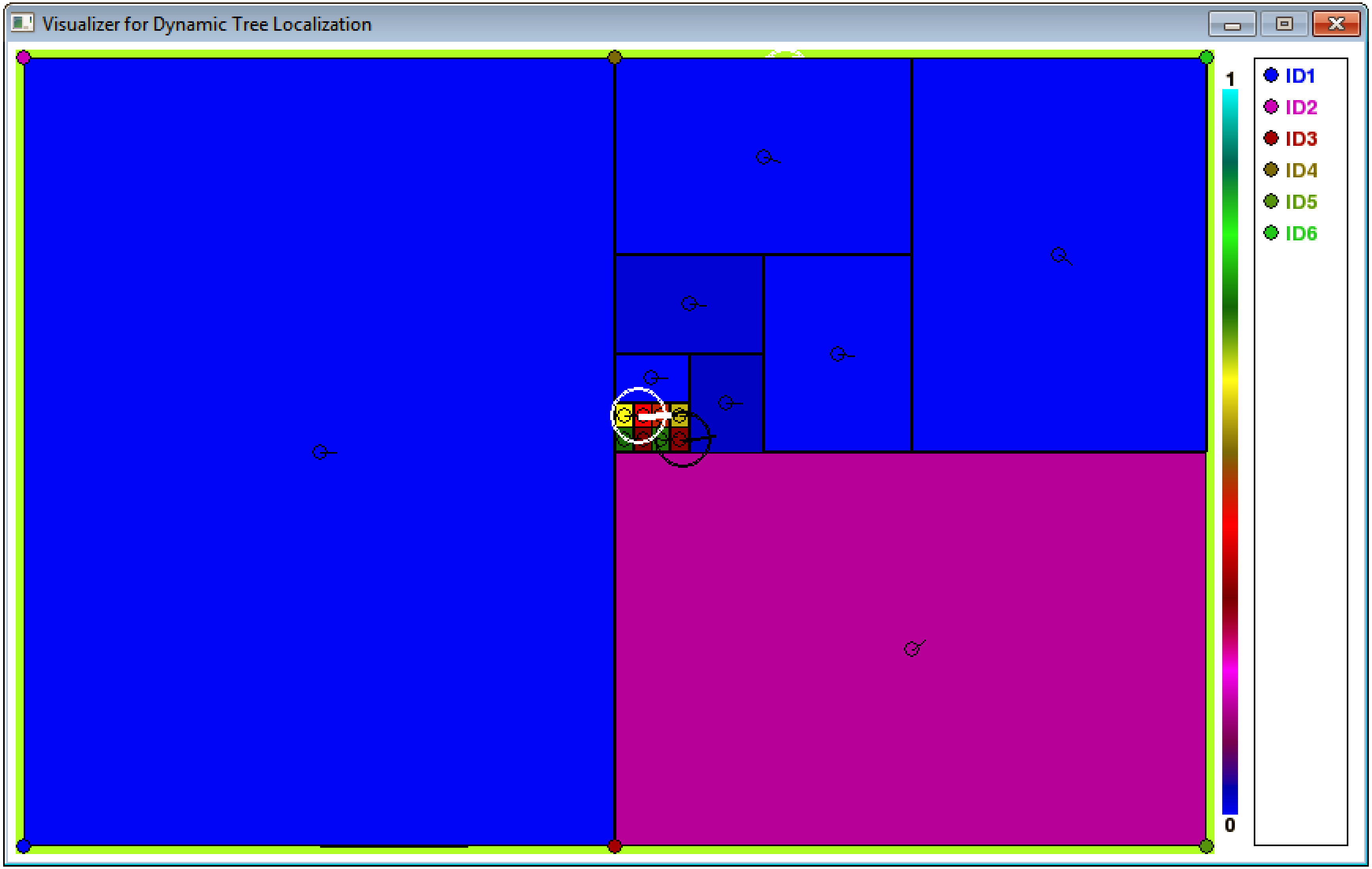
Localization

Used Method	Pro's	Con's	Teams using
(augmented) MCL	Proven to be accurate, Can handle kidnap problem, Can handle complex belief.	Comp. expensive!	Austrian-Kangaroos, B-Human, Cerberus, Edinferno, Noxious-Kouretes, TJArk
MCL & MOsr	Better results than MCL/sr		CMurfs
MCL & neg. Inf.	Faster elimination of particles than MCL		TT-UT Austin Villa
MCL & KF	Less comp. exp. than MCL		rUNSWift
AUX PF & SIR			SPQR+UChile
distance to goal poles	Simple	Not accurate	L3M, NTU RobotPal
UKF & MH	Smooth and performs well		Nao Devils Dortmund
multiple EKFs	Low computation cost		SPIteam
Constraint localization	Low computational cost, More adequate than PF		Nao Team Humboldt
Rao-Black & KF	Low computational cost Fast (re)localization		UPennalizers
Location Sensitive Behavior	Simple	Reliability issues	Wrighteagle Unleashed!
Local Model	Simple	No communication between the robots	WPI Warriors
Cox &CI & UKF	High potential	Not yet stable	RoboEireann

Table 1: Short overview of used methods in SPL 2011

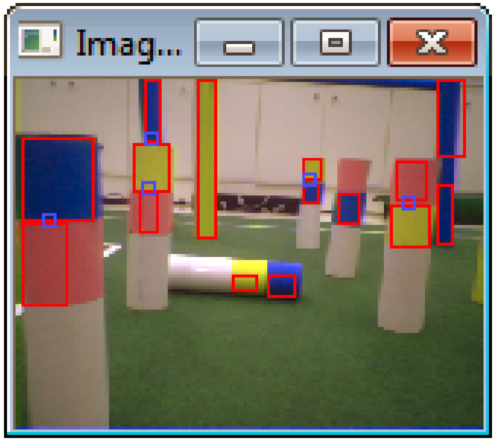
Global localization based on kD tree



Global Localization Algorithm

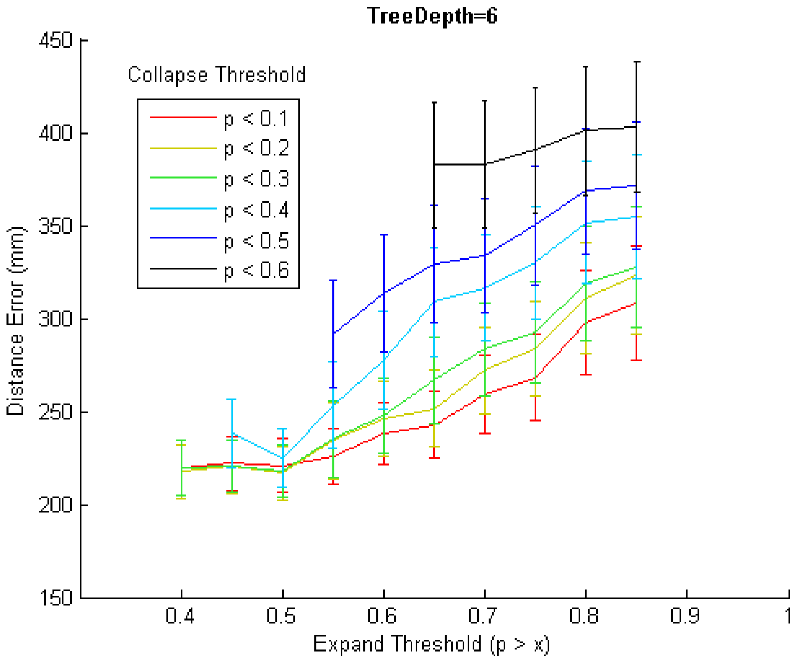
Algorithm 1 Main structure of the Dynamic Tree Algorithm

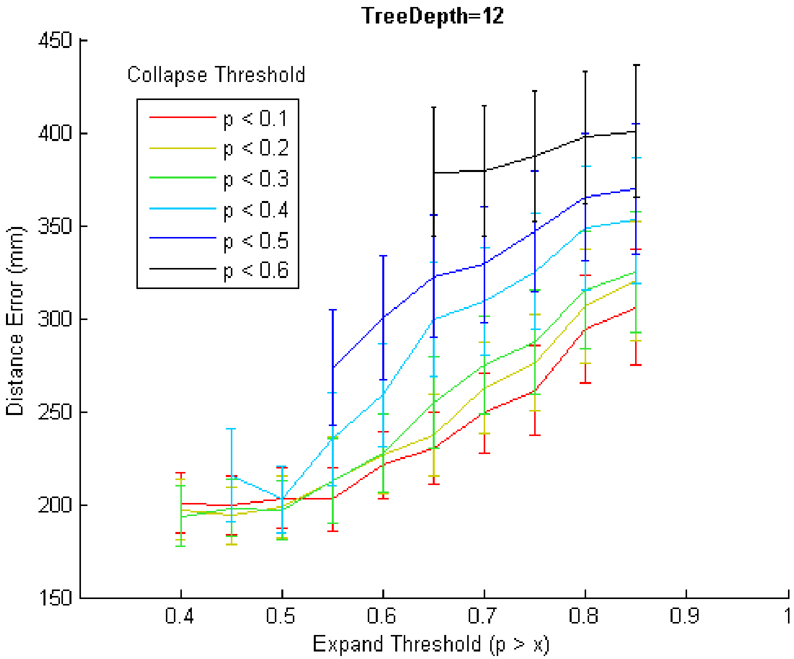
```
tree = CreateRootAndRootChildren()
loop
  observation = GetObservation()
  tree = UpdateTree(tree, observation)
  tree = CheckCollapse(tree)
  tree = CheckExpand(tree, maxTreeDepth)
end loop
```



Observations are based on landmark detection

Results





tree depth	block size	best absolute error
6	187 x 250 mm	220 mm
8	94 x 125 mm	194 mm
10	47 x 63 mm	193 mm
12	23 x 31 mm	193 mm

- Expand Threshold → 0.45
- Collapse Threshold → 0.2

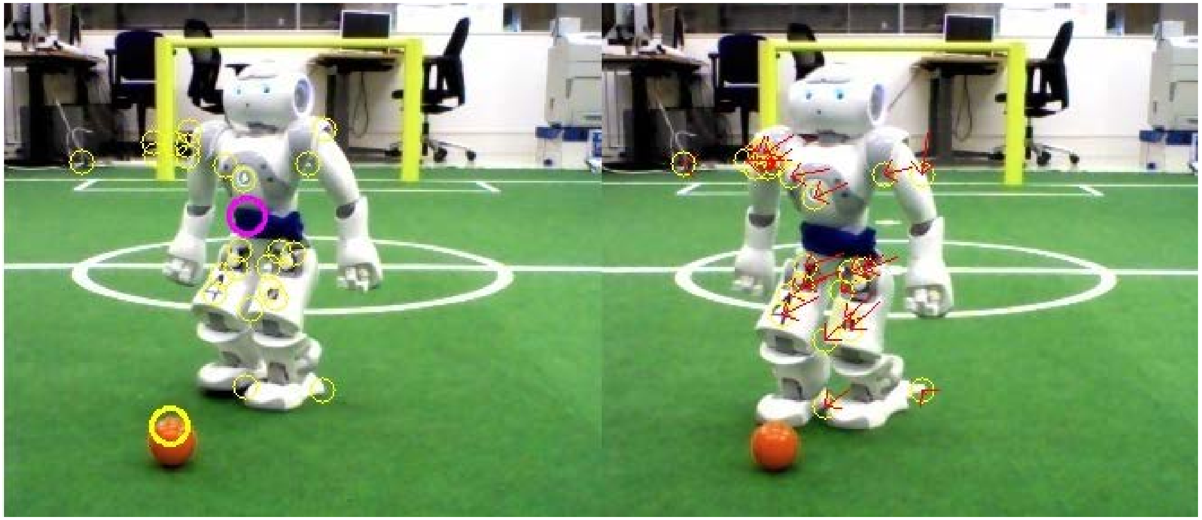
tree depth	time taken	95% confidence
6	4.0 sec	0.9 sec
8	4.1 sec	0.8 sec
10	4.8 sec	1.2 sec

Resumé

Dynamic Tree Localization has the advantage:

- All possible states are incorporated
- Handles kidnapping in natural way
- Can handle multiple hypotheses
- Fast converge fast to small regions

Recognizing Attack Patterns
Clustering of Optical Flow Vectors



Auke Wiggers

Bachelor thesis Artificial Intelligence, June 2012

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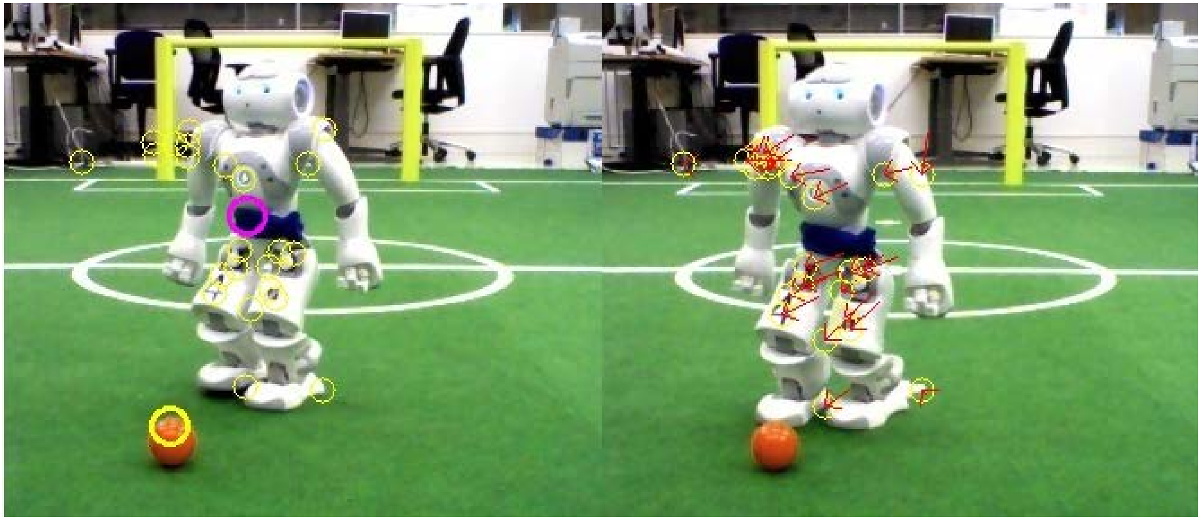
Methodology

- The approach is divided into three steps:
- Calculating optical flow (computer vision)
- Finding patterns (machine learning)
- Detecting patterns in real scenes (computer vision and classification)

Optical flow



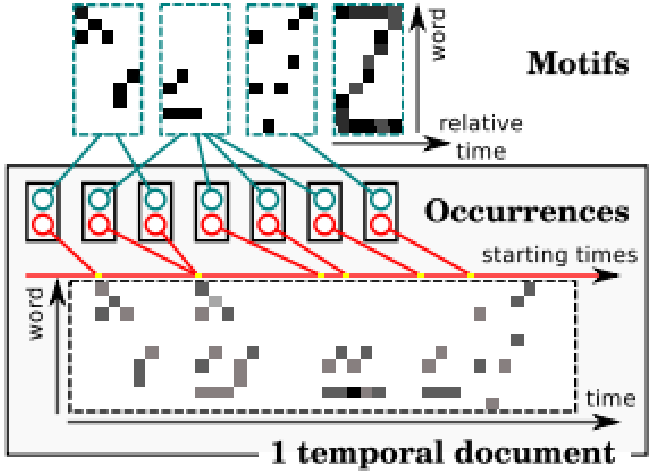
- Optical flow in regions close to the waistband and the ball are selected.

Temporal documents

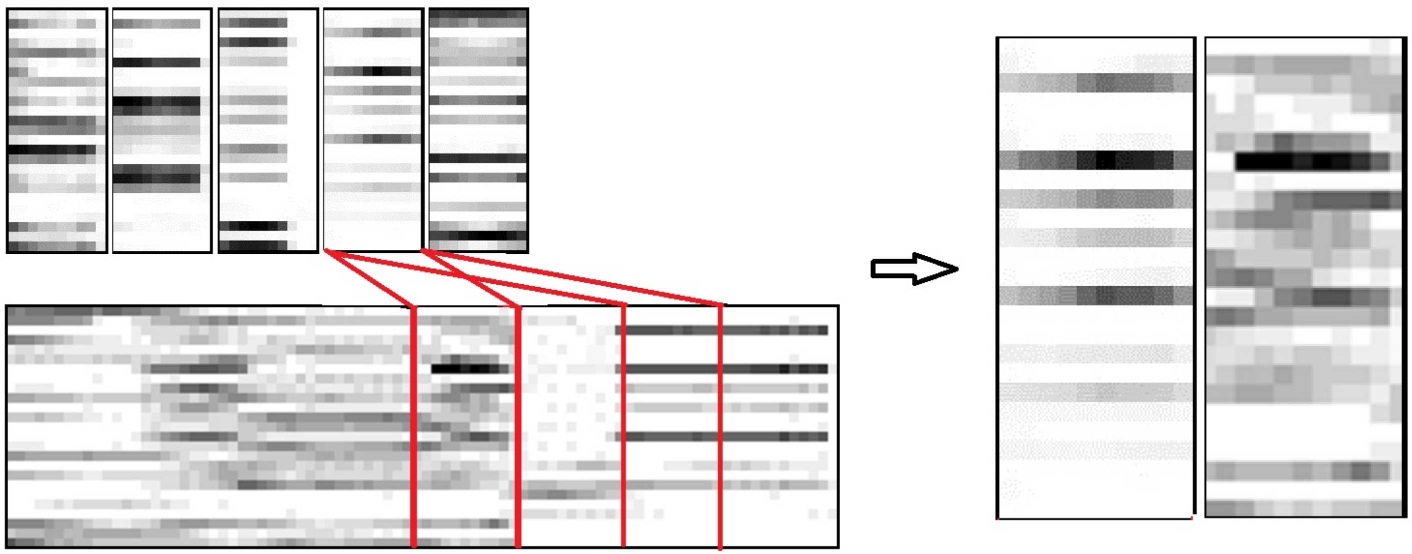
Optical flow vectors:

1. Quantized into categories (up, down, left and right)
2. Location quantized into cells of 10x10 pixels
3. Converted to bag-of-words representation
4. Bag-of-words indexed by timestep

Result: A temporal document.

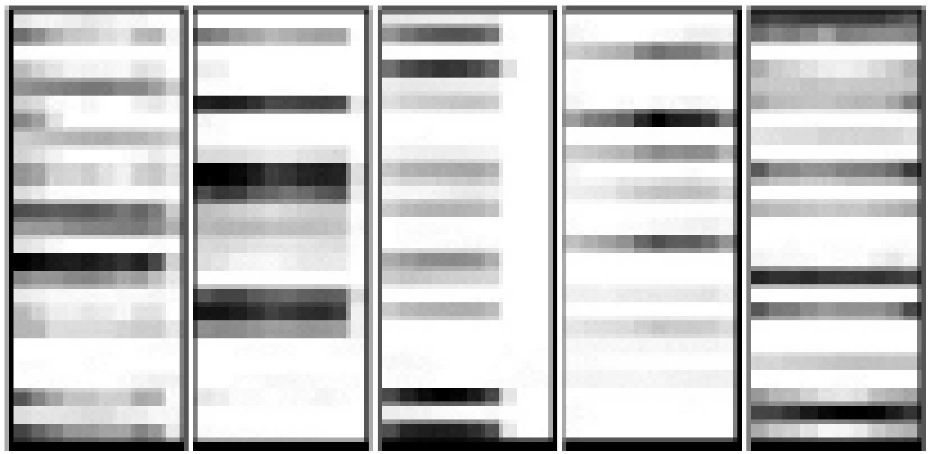


Dimensionality Reduction



Probabilistic Latent Sequential Matching II used to reduce to 25 latent classes.

Prediction / Anticipation



Each document is compared to one of the 5 learned motifs.

If the same motif is selected for several sequential timesteps, the corresponding action is selected: *walk, dive*

Experiments

- Performance tested through 15 penalty shootouts, for various *Nz* and *Tz* .

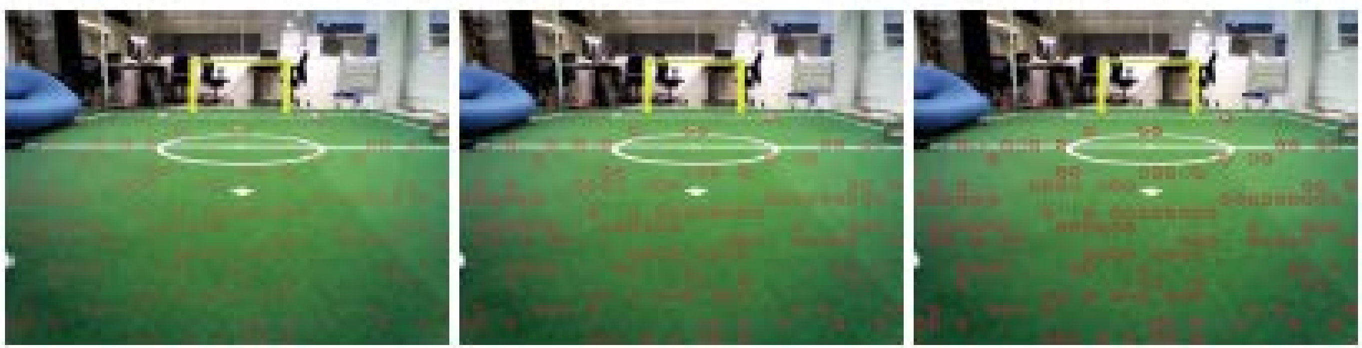
Results

N_z / T_z	Hit	Miss	Goalkeeper interferes
5 / 10	8	3	4
5 / 20	9	4	2
10 / 10	9	3	3
10 / 20	11	4	0

- A limited set of motifs and timestep works bests.

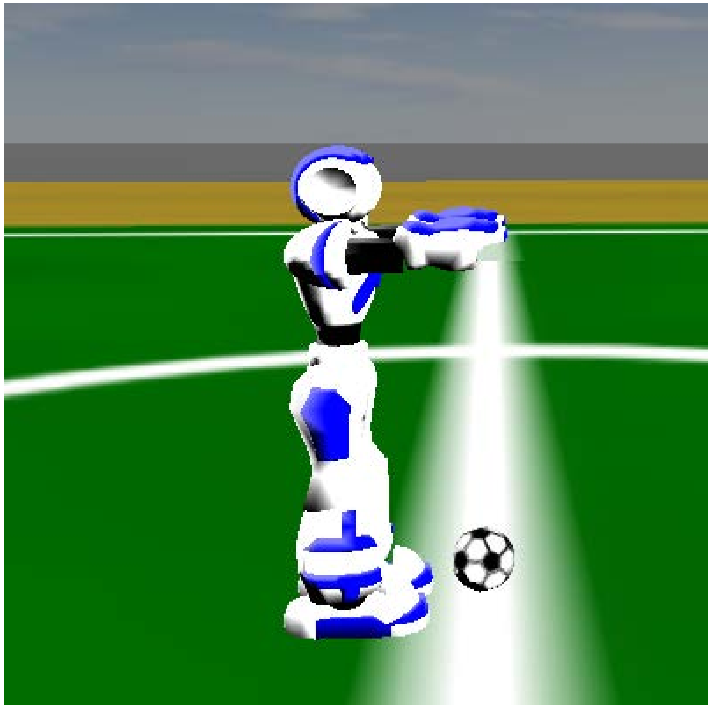
Resumé

- Effectiveness of activity mining is shown
- Machine Learning doesn’t outperform a heuristic approach.



Getting a kick out of humanoid robotics

Using reinforcement learning to shape a soccer kick



Christiaan W. Meijer

Master thesis, Universiteit van Amsterdam, July 2012

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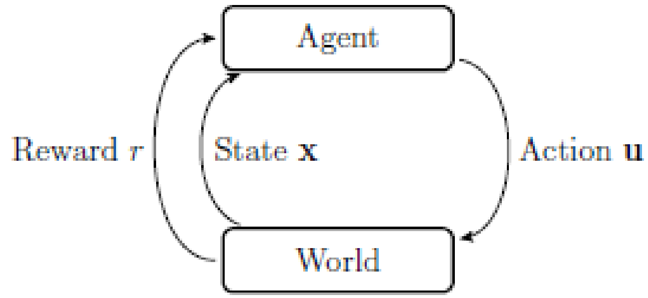
Machine Learning approach



- Find the parameters $\boldsymbol{\theta}_*$ of the optimal policy (combination of actions which the highest cumulative reward)

$$\boldsymbol{\theta}_* = \underset{\boldsymbol{\theta}\in\Theta}{\operatorname{argmax}}\, J(\boldsymbol{\theta}) \qquad \boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_t)$$

- To find the parameters one has to estimate the gradient $\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_t)$

Algorithm 1 Policy gradient

$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta}_{\text{start}}$
repeat
  estimate $\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_t)$
  $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta}_t + \alpha \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_t)$
until stopping criteria are met
return $\boldsymbol{\theta}$

Machine Learning techniques

- Finite difference:

$$[\mathrm{g}_{\mathrm{FD}}^{T}\hat{J}(\boldsymbol{\theta})]^{T} = (\Delta\Theta^{T}\Delta\Theta)\Delta\Theta^{T}\hat{J}$$

- To find the parameters $\boldsymbol{\theta}_*$, one has to estimate the gradient

$$\boldsymbol{\theta}_* = \operatorname*{argmax}_{\boldsymbol{\theta}\in\Theta} J(\boldsymbol{\theta}) \qquad \boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha\nabla_{\boldsymbol{\theta}}J(\boldsymbol{\theta}_t)$$

$$\nabla_{\boldsymbol{\theta}}J(\boldsymbol{\theta}_t)$$

Algorithm 1 Policy gradient

```
θ ← θ_start
repeat
    estimate ∇_θ J(θ_t)
    θ ← θ_t + α∇_θ J(θ_t)
until stopping criteria are met
return θ
```

Rewards

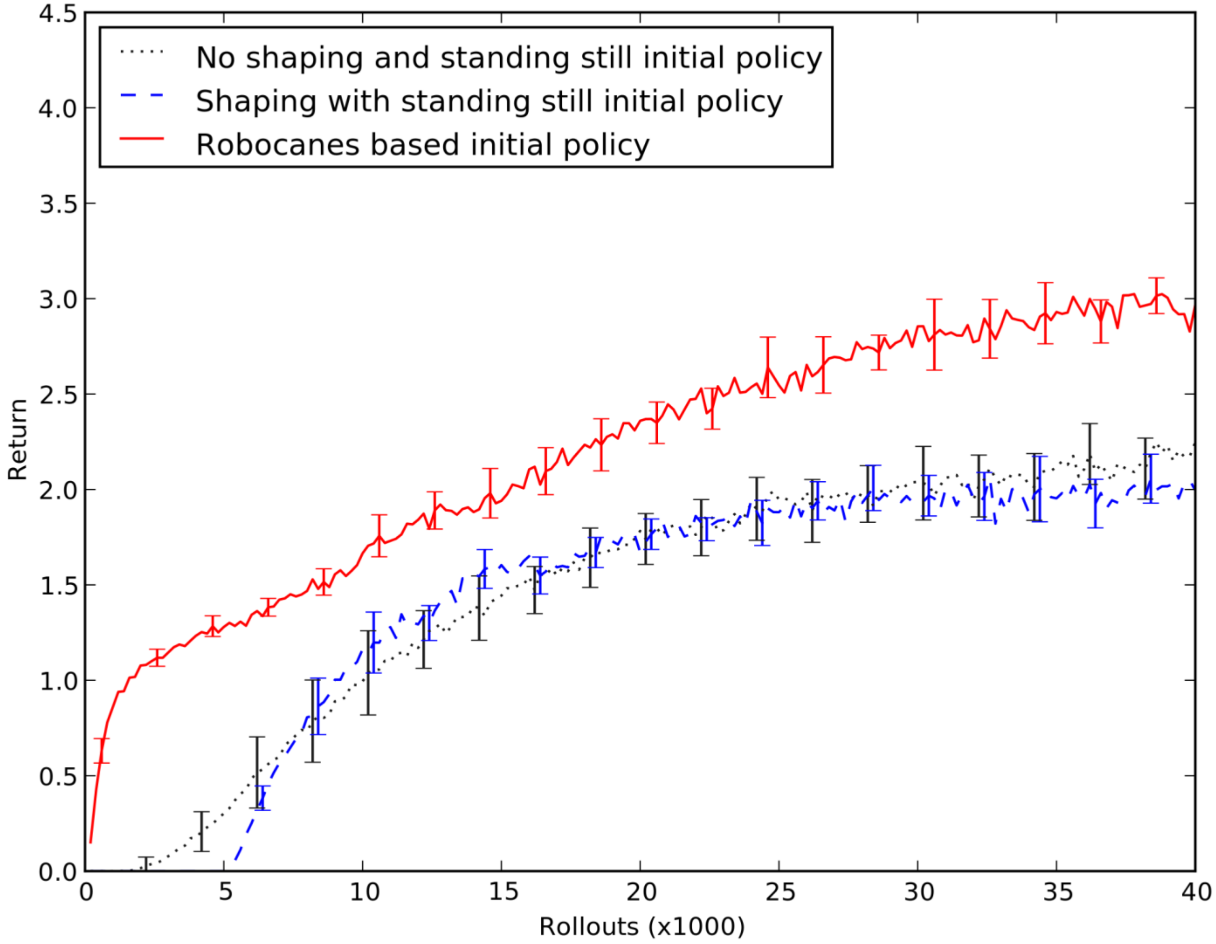
- Stand on one leg:

$$f_{\text{foot\_pressure}}(p_l, p_r, t) = \begin{cases} p_r - p_l, & \text{if } 1.0 < t < 1.5 \\ 0, & \text{otherwise} \end{cases}$$

- Shoot without falling:

$$f_{\text{proportional}}(x) = f_{\text{max\_ball\_velocity}}(x)(1 + \mathrm{w} f_{\text{torso\_angle}}(x))$$

Results



No shaping and standing still initial policy
Shaping with standing still initial policy
Robocanes based initial policy
Return
Rollouts (x1000)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
0
5
10
15
20
25
30
35
40

Kicks

robocanes edited.mpg

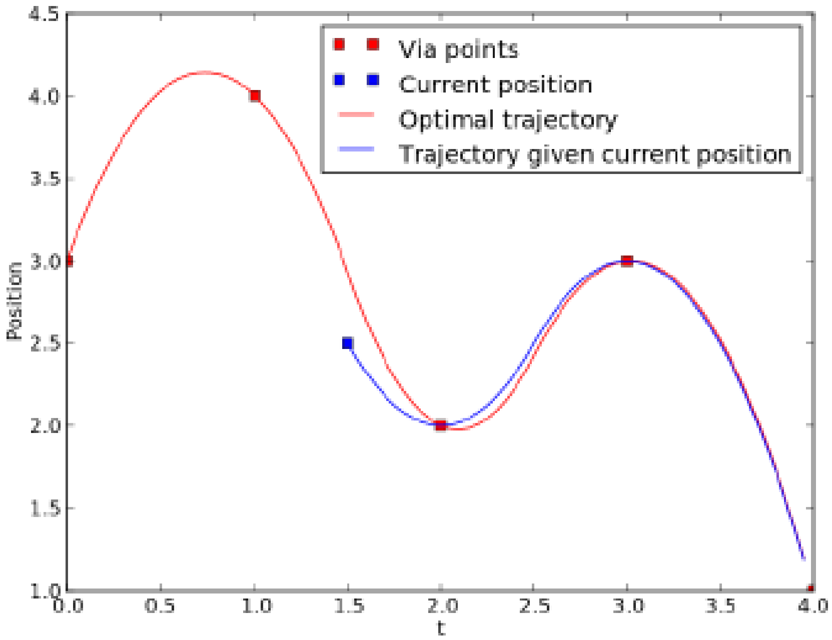
oneleg edited.mpg

optimized edited.mpg

balanced edited.mpg

Resumé

- Finite Difference was most stable method
- Shaping didn't give a boost
(although it helped stability)



Conclusion

- A humanoid robot has much to learn

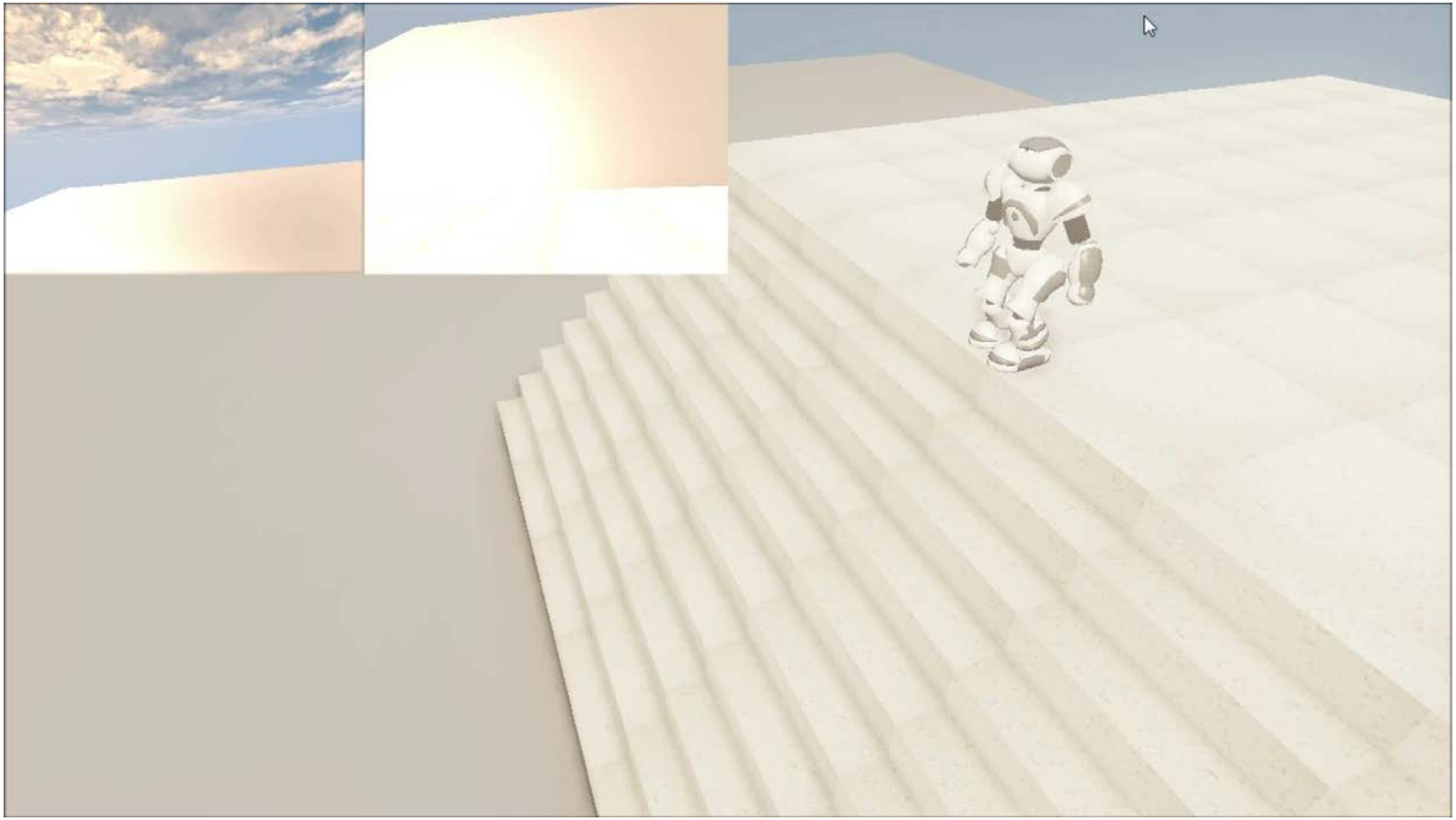
- The correspondence to a human makes it possible to project emotions on the robot and understand its perspective

Publications

2012

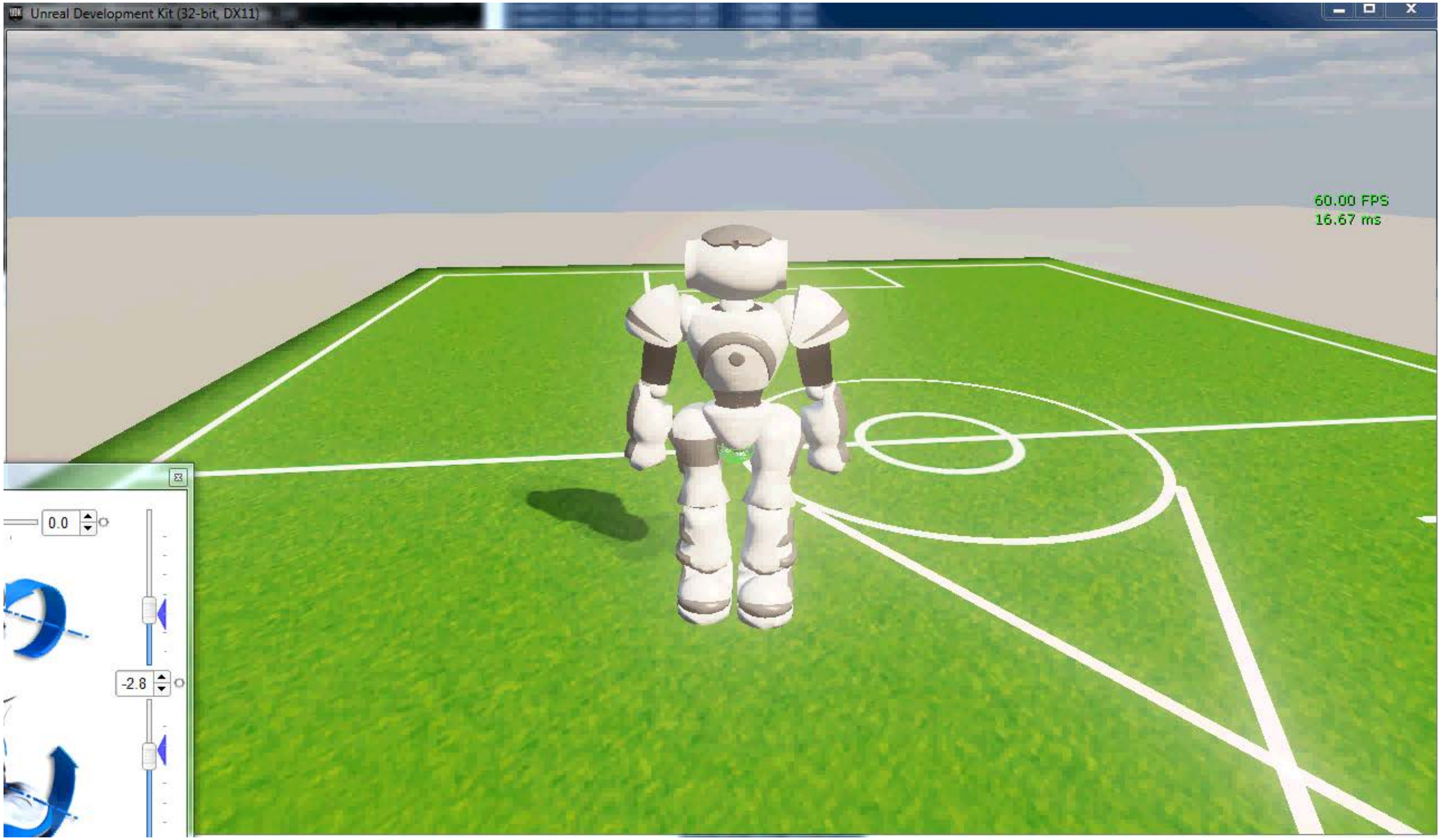
- Sander Nugteren, *Nao Recognition and coordination*, Project report, Universiteit van Amsterdam, August 2012.
- Becht, Inge, Maarten de Jonge, and Richard Pronk. *A Dynamic Kick for the Nao Robot*. Project Report. Universiteit van Amsterdam. July 26, 2012.
- Christiaan Meijer, *Getting a kick out of humanoid robotics : Using reinforcement learning to shape a soccer kick*, Master's Thesis, Universiteit van Amsterdam, July 2012.
- Auke J. Wiggers, *Recognizing Attack Patterns: Clustering of Optical Flow Vectors in RoboCup Soccer*, Bachelor's Thesis, Universiteit van Amsterdam, June 2012.
- Sander van Noort and Arnoud Visser, *Extending Virtual Robots towards RoboCup Soccer Simulation and @Home*, Proceedings of the 16th RoboCup Symposium, Mexico, June 2012. To be published in the Springer Lecture Notes on Artificial Intelligence series.
- Camiel Verschoor, Duncan ten Velthuis, Auke Wiggers, Michael Cabot, Anna Keune, Sander Nugteren, Hendrik van Egmond, Hessel van der Molen, Richard Rozeboom, Inge Becht, Maarten de Jonge, Richard Pronk, Chiel Kooijman, and Arnoud Visser, Dutch Nao Team – Team Description for RoboCup 2012, to be published on the Proceedings CD of the 16th RoboCup Symposium, Mexico, June 2012
- Sander van Noort, Validation of the dynamics of a humanoid robot in USARSim, Master's thesis, Universiteit van Amsterdam, May 2012.
- Sander van Noort and Arnoud Visser, Validation of the dynamics of an humanoid robot in USARSim, Proceedings of the Performance Metrics for Intelligent Systems Workshop (PerMIS'12), March 2012.
- Duncan ten Velthuis, Camiel Verschoor, Auke Wiggers, Michael Cabot, Anna Keune, Sander Nugteren, Hendrik van Egmond, Tim van Rossum, Hessel van der Molen, Richard Rozeboom, Inge Becht, Maarten de Jonge, Richard Pronk, Chiel Kooijman, Roman Slaap and Arnoud Visser, Dutch Nao Team – Team Description for Robocup 2012 – Mexico City, Mexico, Amsterdam, January 11, 2012.

Disclaimer

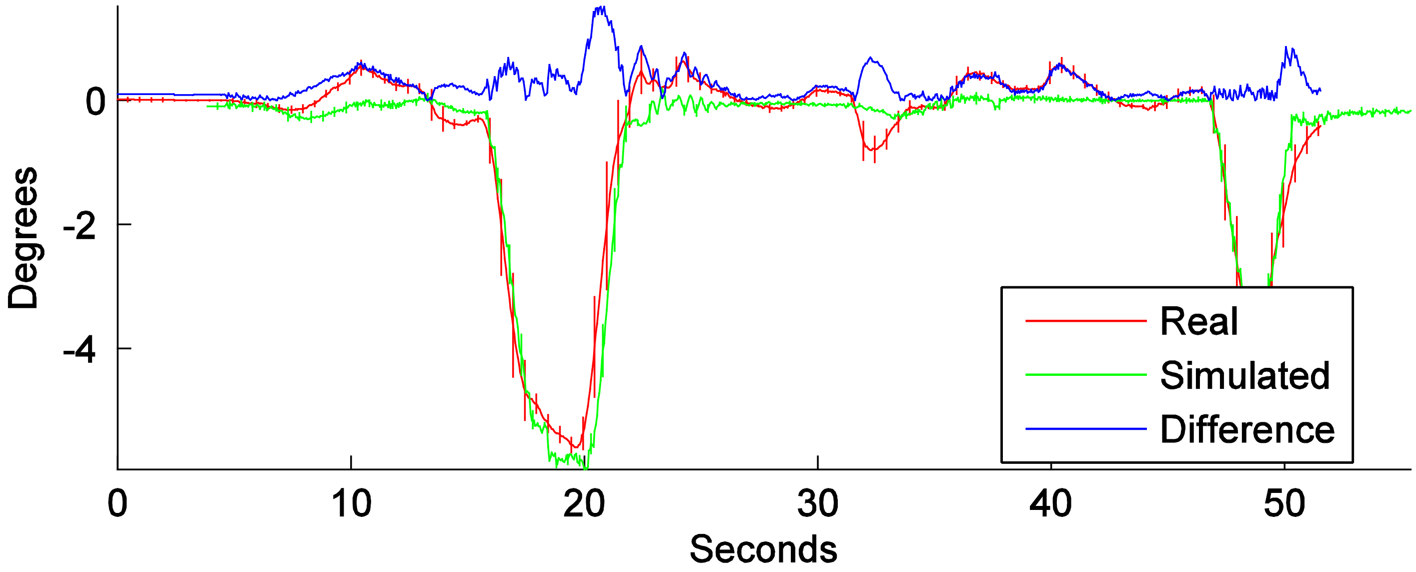


Quite some Nao robots got hurt during this research

Tai Chi Chuan



Tai Chi Chuan

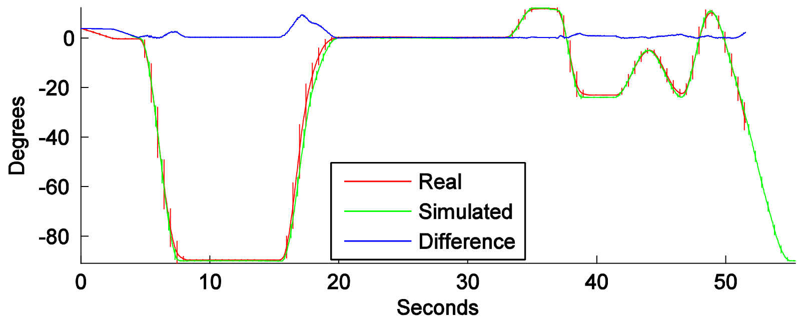


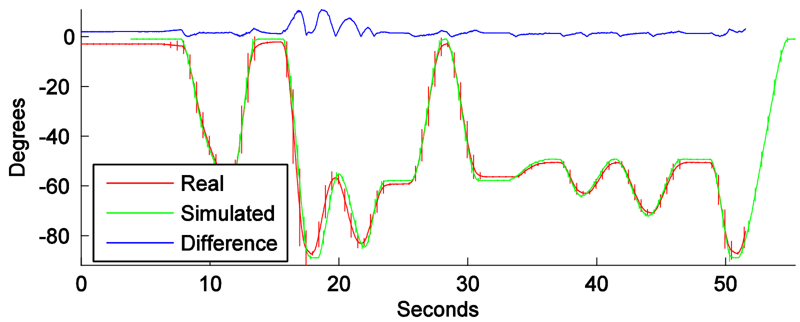
Movement of the Right Hip (yaw / pitch):

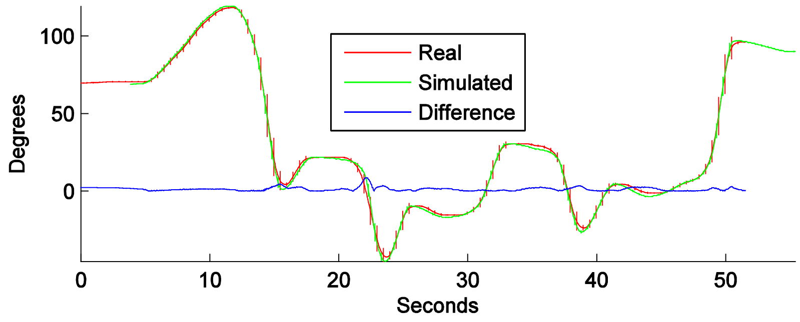
•Good correspondence, except for deceleration

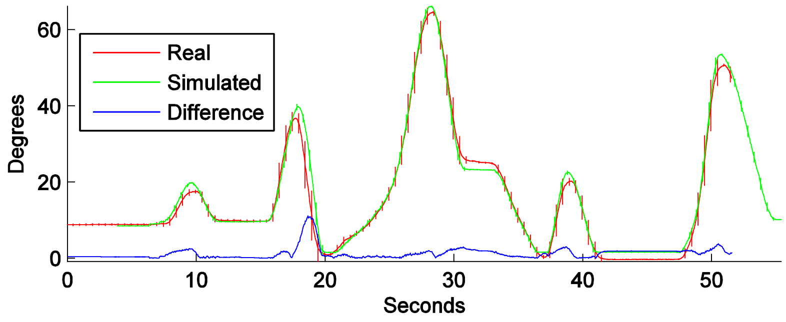
•Differences in the order of natural variance

Upper body during Tai Chi Chuan



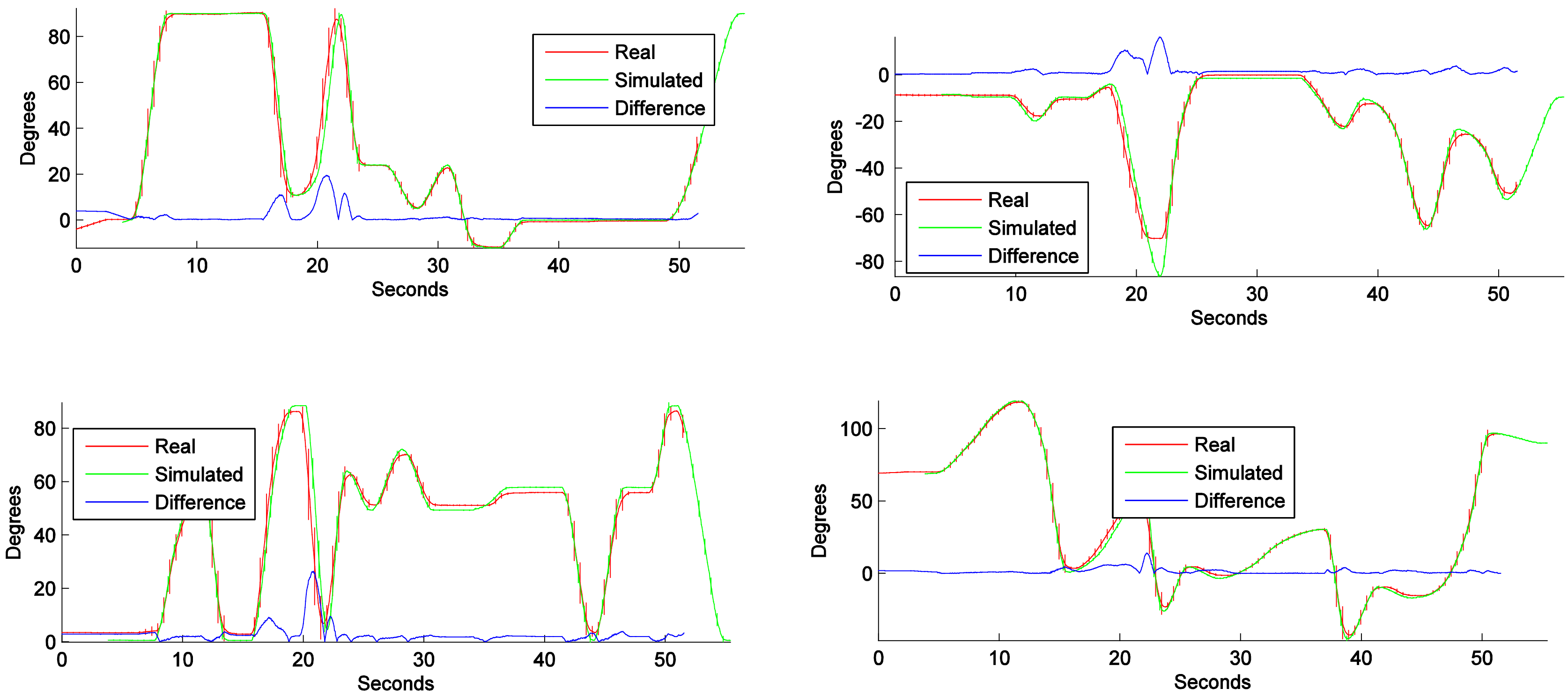






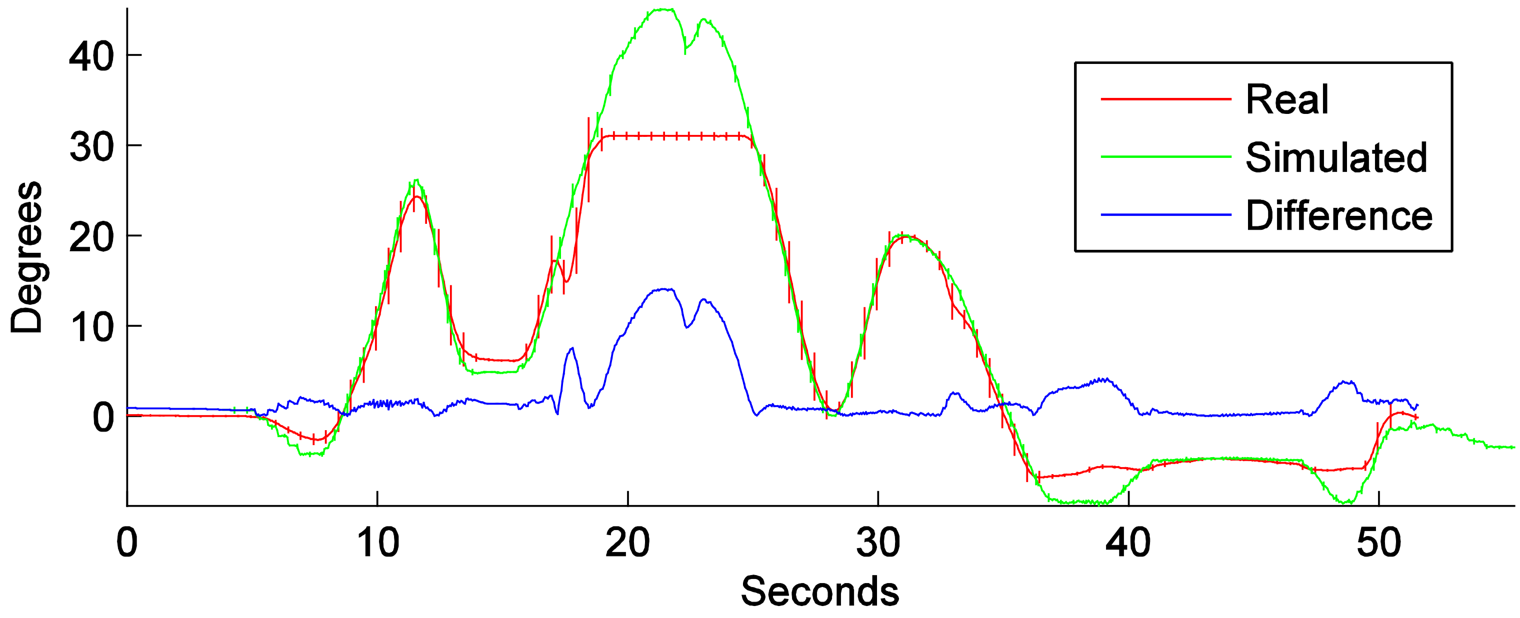
Left side

Upper body during Tai Chi Chuan



Right side

Tai Chi Chuan

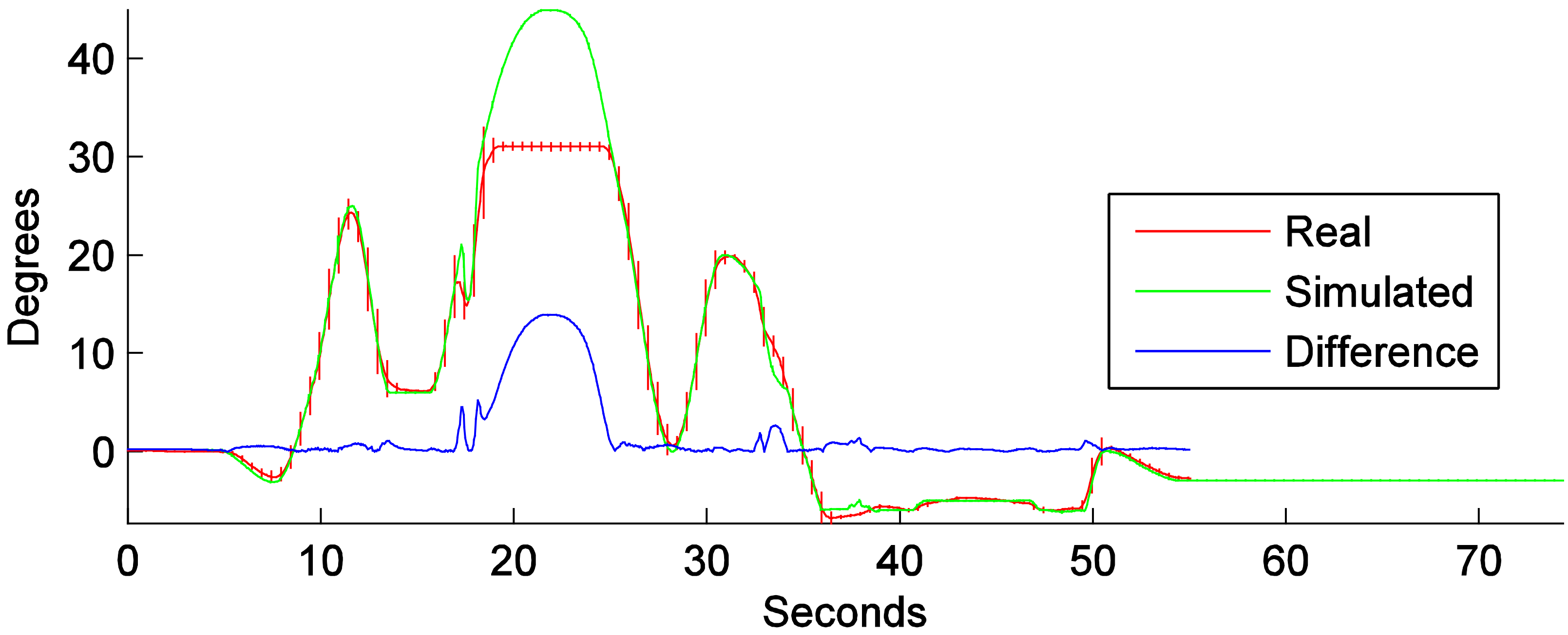


Movement of the Right Ankle (roll):

•Good correspondence, except halfway experiment

•Again hardware limits for combination roll / pitch encountered

Tai Chi Chuan



Movement of the Right Ankle (roll) for NaoSim:

•Also for the official simulator the hardware limits are not modeled

Validation of the dynamics of an humanoid robot in USARSim

Sander van Noort & Arnoud Visser

Performance Metrics for Intelligent Systems workshop (PerMIS'12),
College Park, MD, March 2012

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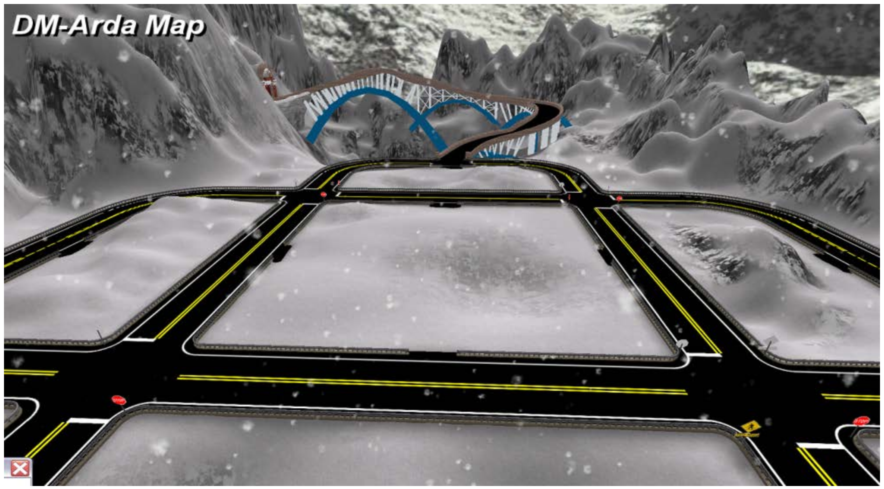
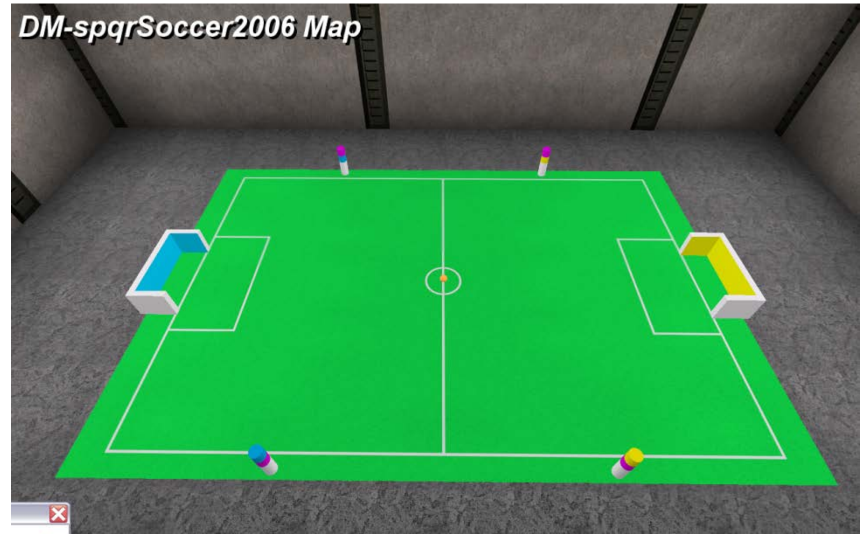
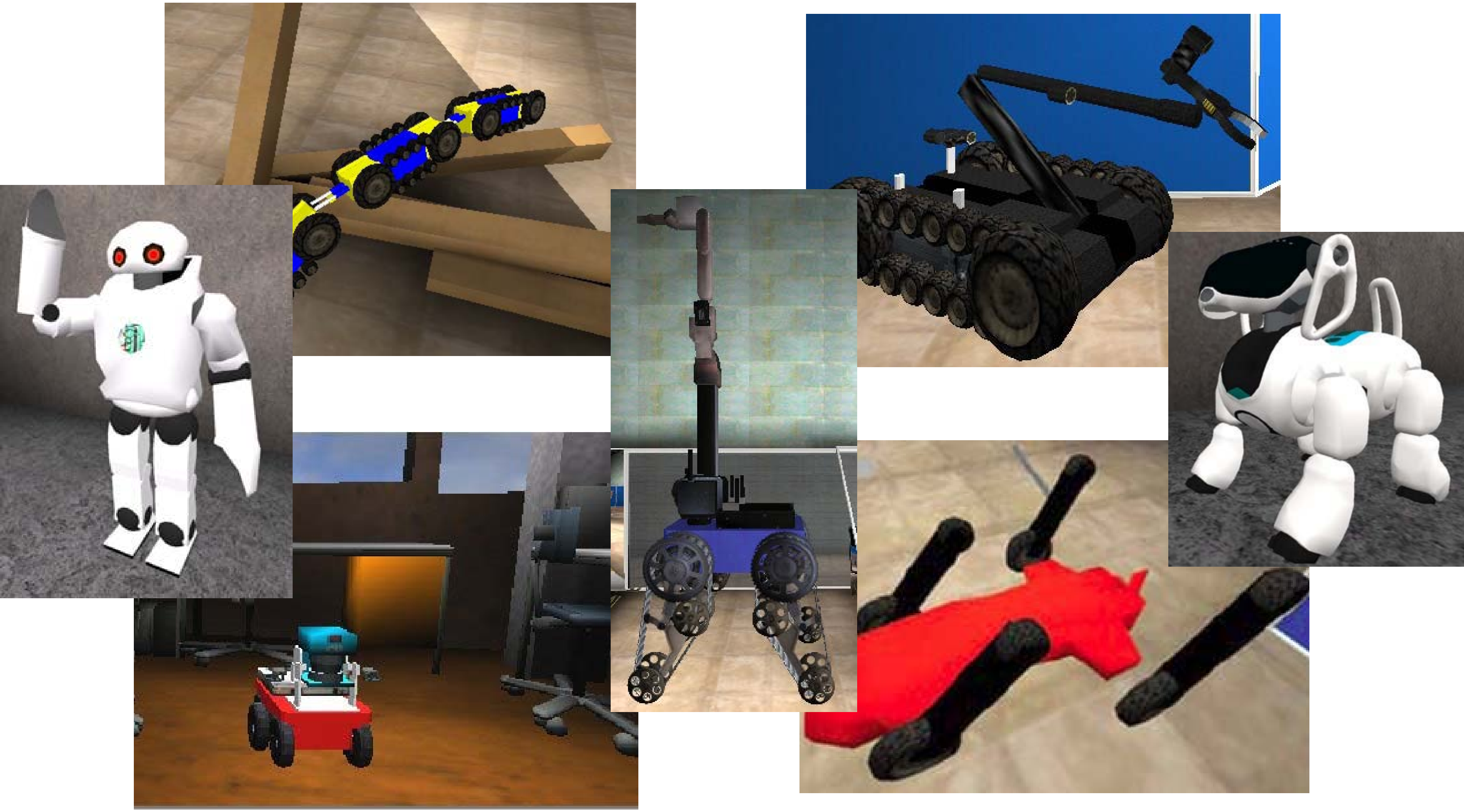
USARSim: A wide variety of worlds

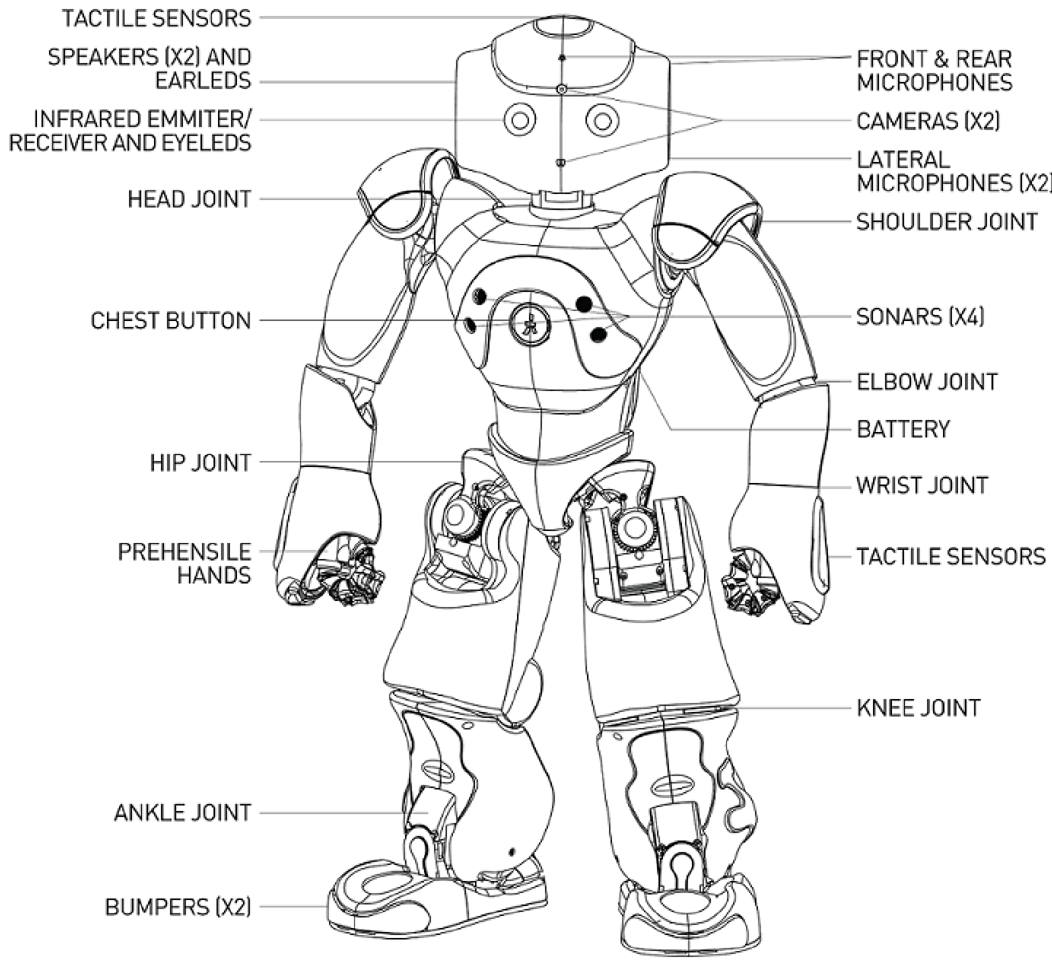




USARSim: A wide variety of Robots

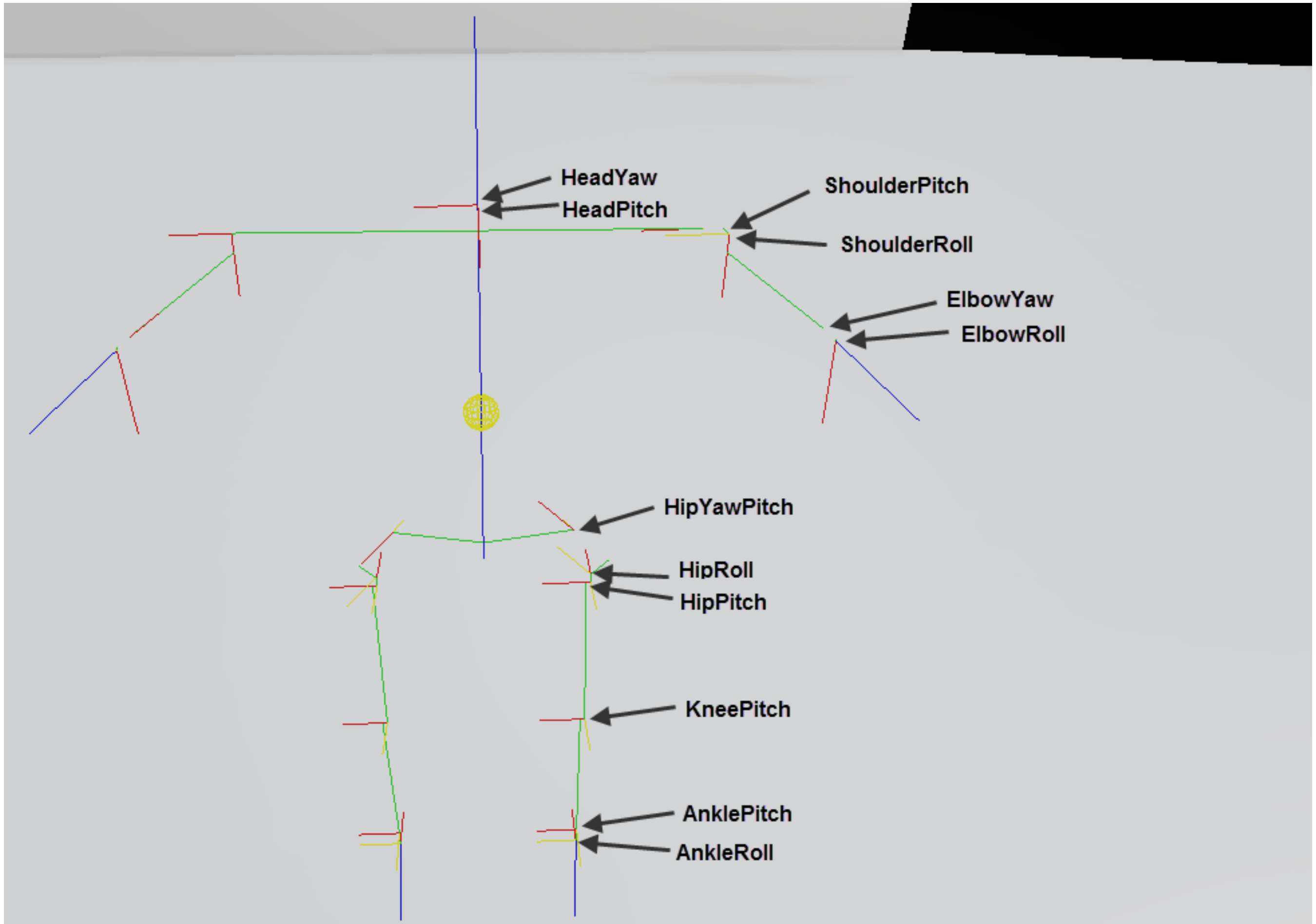


Humanoid robot NAO



Aldebaran Robotics, France

Constrained Kinematic Chains



5 Kinematic chains; 21 Degrees of Freedom.

Denavit Hartenberg representation

- Offset and range of each joint

$$LHipYawPitch = \begin{bmatrix} \cos\theta_1 & -\frac{1}{4}\pi\sin\theta_1 & \frac{1}{4}\pi\sin\theta_1 & 0.0461\cos\theta_1 \\ \sin\theta_1 & \frac{1}{4}\pi\cos\theta_1 & -\frac{1}{4}\pi\cos\theta_1 & 0.0461\cos\theta_1 \\ 0 & \frac{1}{4}\pi & \frac{1}{4}\pi & 0.07 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LShoulderPitch = \begin{bmatrix} \cos\theta_1 & 0 & \sin\theta_1 & 0.0900\cos\theta_1 \\ \sin\theta_1 & 0 & -\cos\theta_1 & 0.0900\cos\theta_1 \\ 0 & 1 & 0 & 0.08 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LShoulderRoll = \begin{bmatrix} \cos\theta_2 & 0 & \sin\theta_2 & 0.0100\cos\theta_2 \\ \sin\theta_2 & 0 & -\cos\theta_2 & 0.0100\cos\theta_2 \\ 0 & 1 & 0 & 0.01 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LElbowYaw = \begin{bmatrix} \cos\theta_3 & 0 & \sin\theta_3 & 0.1097\cos\theta_3 \\ \sin\theta_3 & 0 & -\cos\theta_3 & 0.1097\cos\theta_3 \\ 0 & 1 & 0 & 0.01 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LElbowRoll = \begin{bmatrix} \cos\theta_4 & 0 & \sin\theta_4 & 0 \\ \sin\theta_4 & 0 & -\cos\theta_4 & 0 \\ 0 & 1 & 0 & 0.00 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LHipRoll = \begin{bmatrix} \cos\theta_2 & 0 & \sin\theta_2 & 0.0134\cos\theta_2 \\ \sin\theta_2 & 0 & -\cos\theta_2 & 0.0134\cos\theta_2 \\ 0 & 1 & 0 & 0.03 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

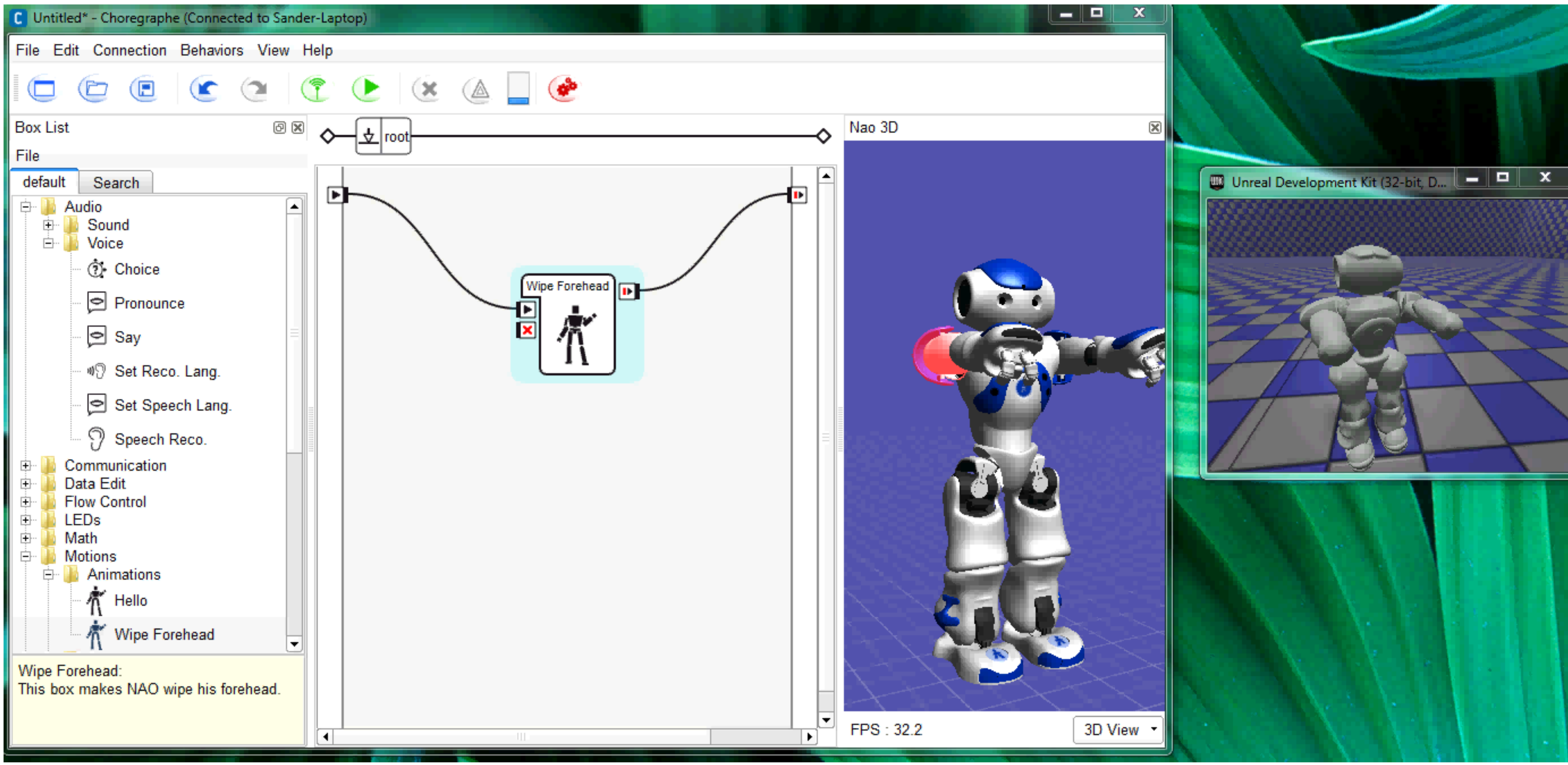
$$LHipPitch = \begin{bmatrix} \cos\theta_3 & 0 & \sin\theta_3 & 0.0050\cos\theta_3 \\ \sin\theta_3 & 0 & -\cos\theta_3 & 0.0050\cos\theta_3 \\ 0 & 1 & 0 & 0.00 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LKneePitch = \begin{bmatrix} \cos\theta_4 & -\sin\theta_4 & 0 & 0.0880\cos\theta_4 \\ \sin\theta_4 & \cos\theta_4 & 0 & 0.0880\cos\theta_4 \\ 0 & 0 & 1 & 0.00 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

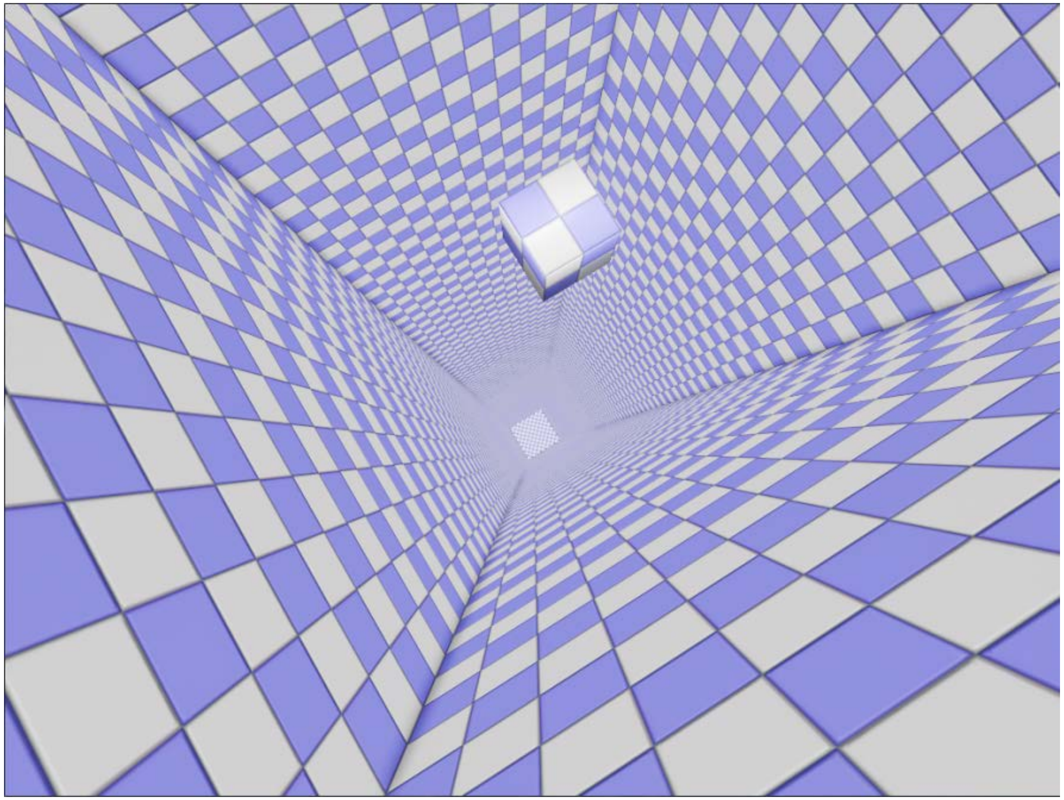
$$LAnklePitch = \begin{bmatrix} \cos\theta_5 & -\sin\theta_5 & 0 & 0.1001\cos\theta_5 \\ \sin\theta_5 & \cos\theta_5 & 0 & 0.1001\cos\theta_5 \\ 0 & 0 & 1 & 0.00 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$LAnkleRoll = \begin{bmatrix} \cos\theta_6 & 0 & \sin\theta_6 & 0.0100\cos\theta_6 \\ \sin\theta_6 & 0 & -\cos\theta_6 & 0.0100\cos\theta_6 \\ 0 & 1 & 0 & 0.00 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Constrained movement of joints



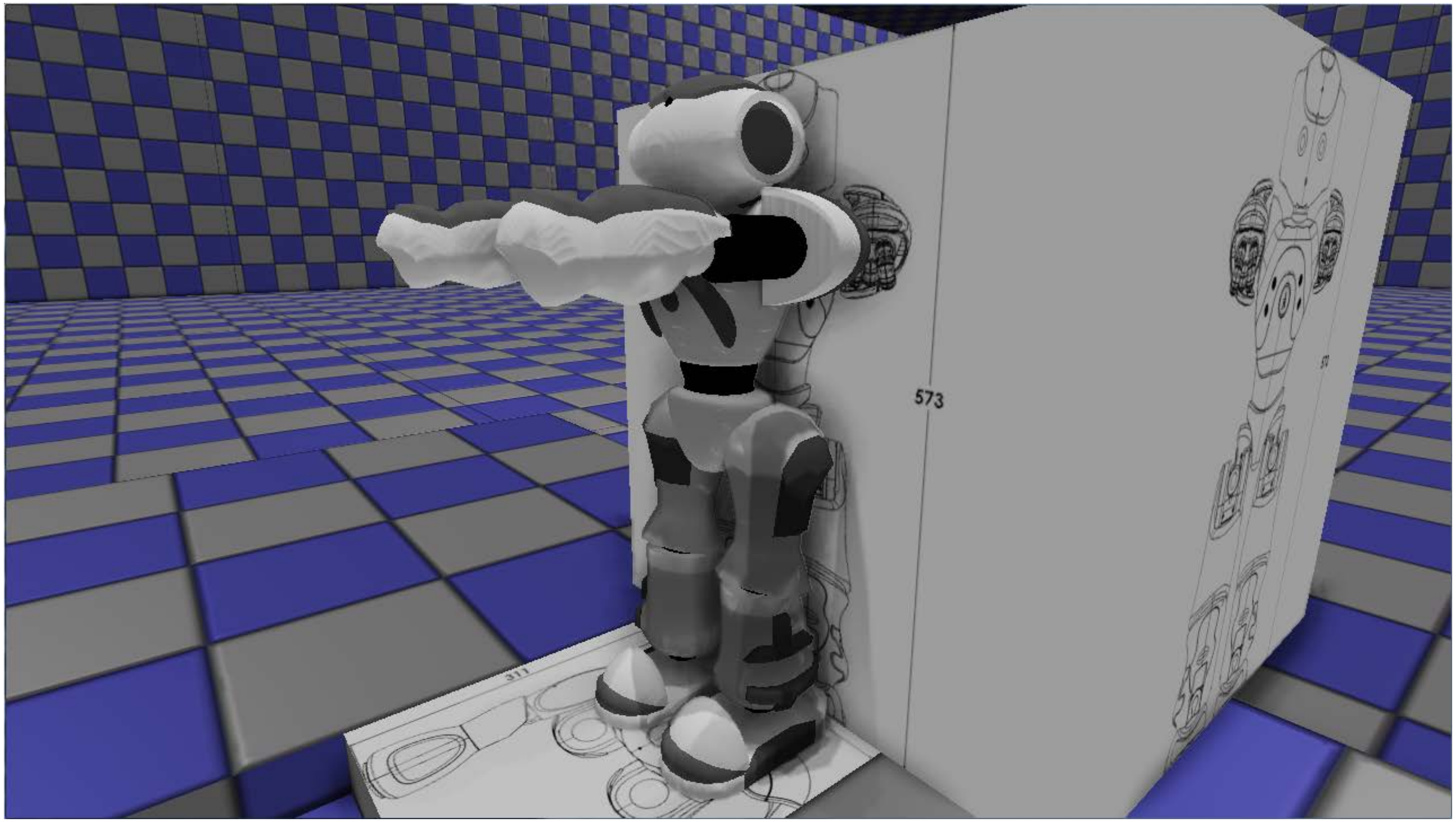
Gravity



Default values for the Unreal Engine had to be corrected with a factor 2.5

G (uu/s) / Dist (uu)	1024	2048	4096	8192	16384	32768
-2452.5uu (rbs 1, ld 0.1)	1.06	1.06	1.08	1.1	1.13	1.19
-2452.5uu (rbs 1, ld 0.0)	1.03	1.02	1.01	1.01	1.01	1.00

Advanced experiments



Three full body movements:
- A kick
- Balance act (Tai Chi Chuan)
- Single step

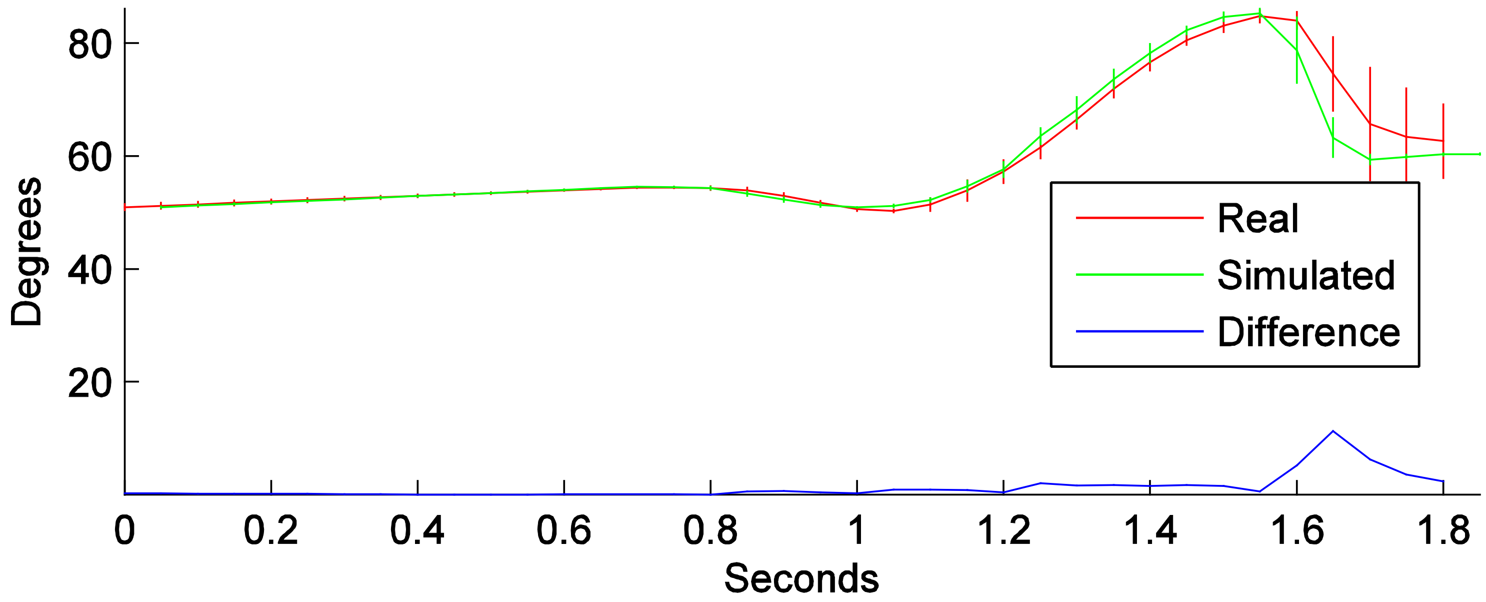
Balance act

Diagnostic movement: Tai Chi Chuan

•Real robot: all motors and joints still functional

•Simulated robot: weight correctly distributed over body

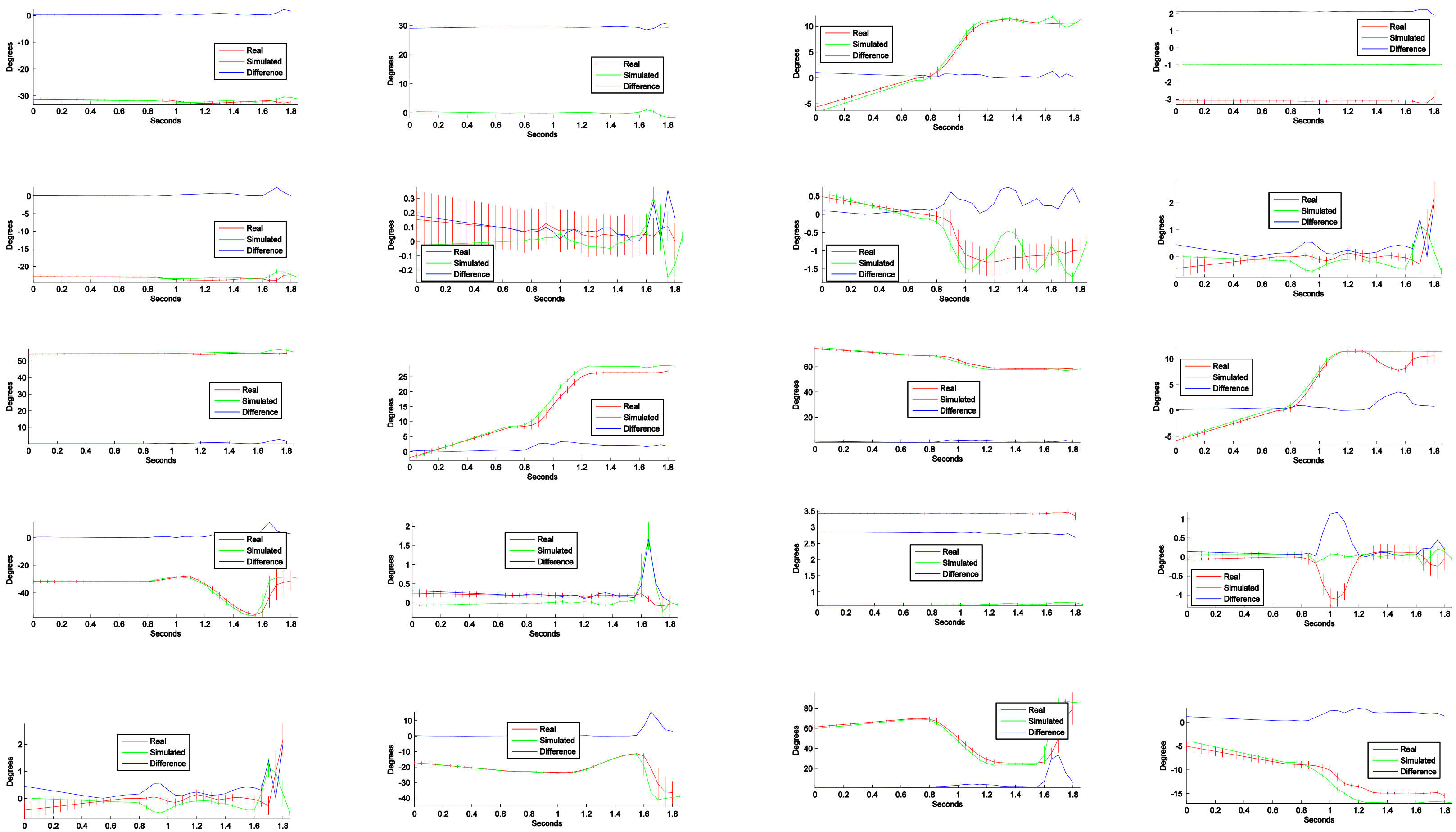
A kick



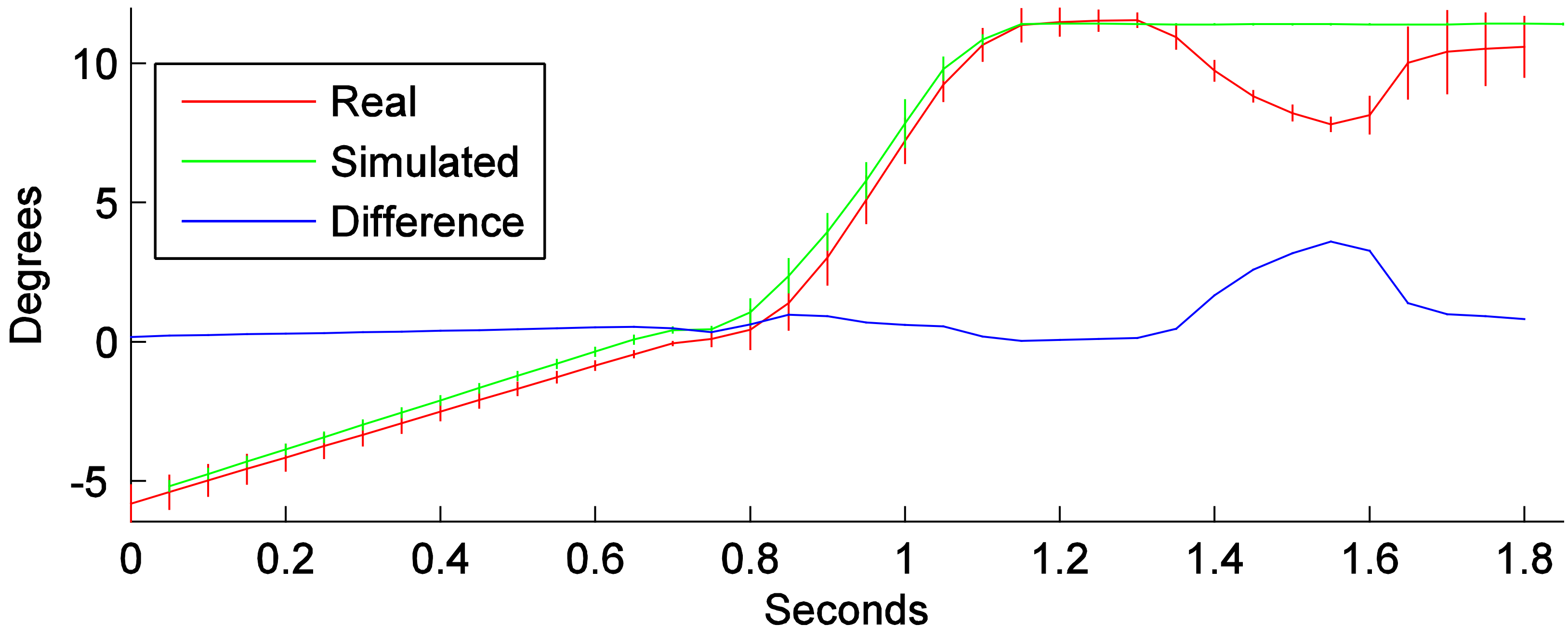
Movement of the Right Knee (pitch):

- Good correspondence, except for deceleration
- More variance with the real robot, compared to the simulated robot

21 joints



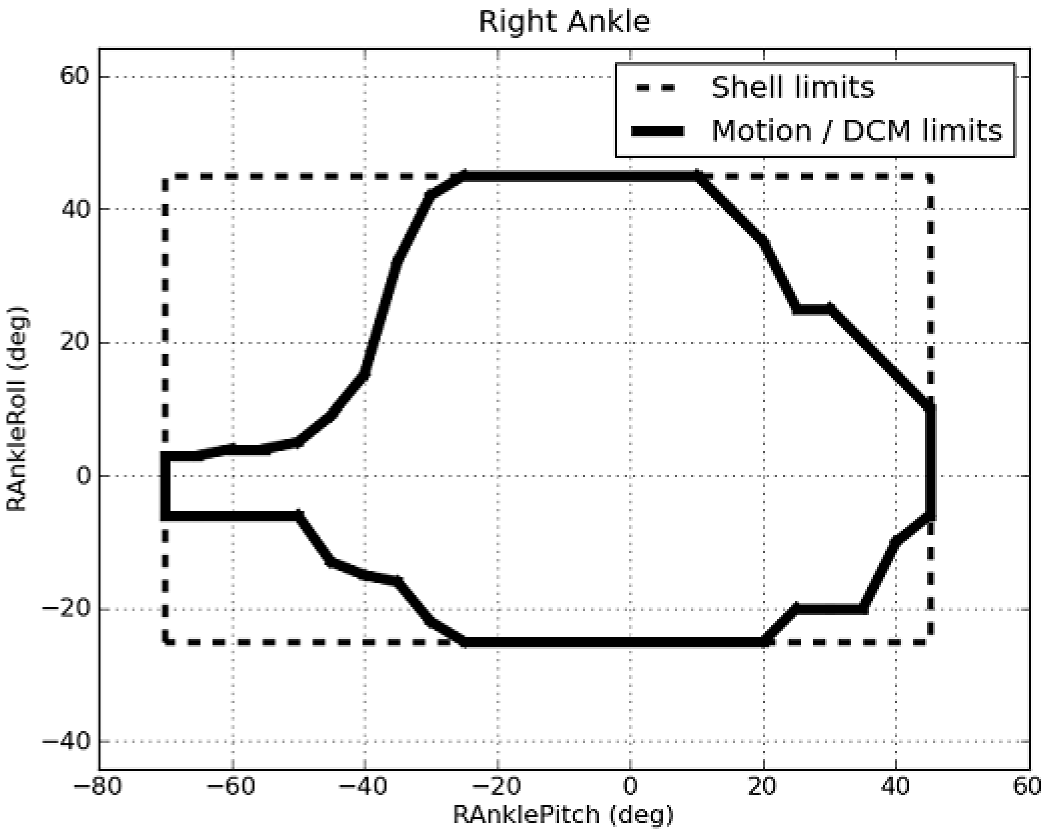
A kick



Movement of the Right Ankle (roll):

- Good correspondence, except for around 1.5 s
- Angle drifts away from requested angle

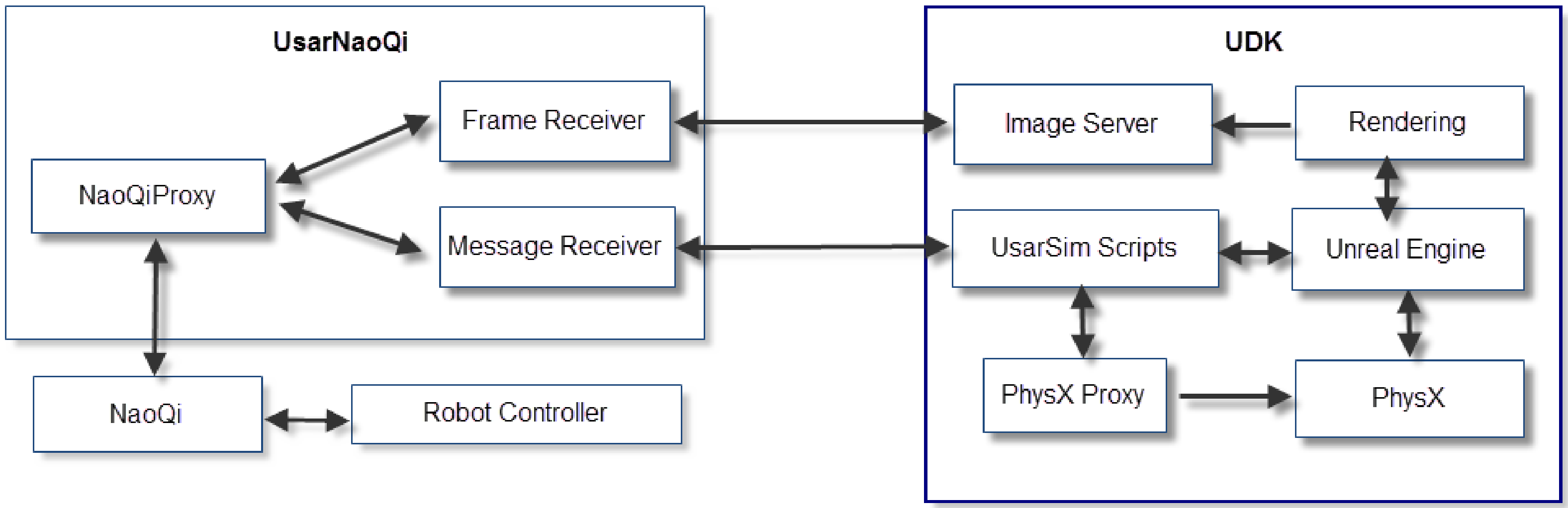
Shell limits



Reason for discrepancy Right Ankle roll during kick:

- Hardware limits, depended on Right Angle pitch

Full application

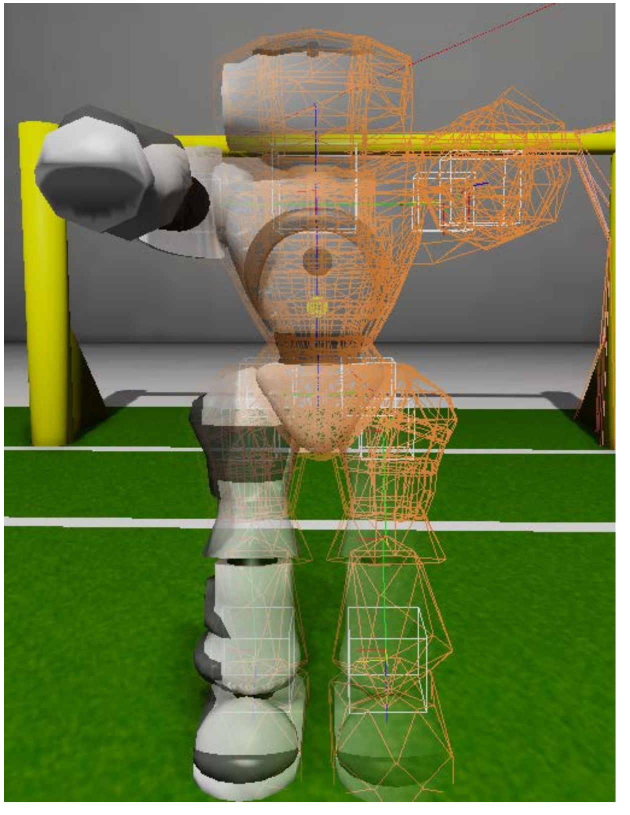


A proxy server was built which allows to command the Nao via its natural interface (NaoQi). NaoQi has e.g. a C++ and Python interface.

RoboCup Soccer

The Python code of an actual RoboCup team (Dutch Nao Team) was used to play a game of soccer.

Resumé

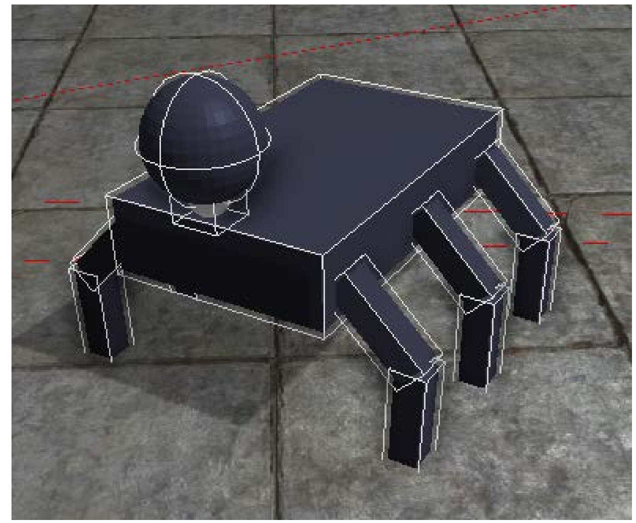


Presented a validated humanoid robot in USARSim UDK

Resumé

Demonstrated a methodology to validate such robot with a sequence of experiments

Resumé



Validated the dynamics of multiple kinetic chains in contact with the ground